# THREE ESSAYS ON ENVIRONMENT, ECONOMICS, AND POLITICS

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# Abstract

This thesis consists of three essays that shed light on different aspects of the relationship between the environment, economic and politics. In the first chapter we consider the deployment of large hydropower dams in Vietnam, an effective infrastructure that converts water resources into clean and inexpensive electricity for the economy, and protects downstream people from floods. The cascade design is shown to make the system more resilient against adverse impacts of climate change. The second chapter estimates the impact of power outages in Vietnam on firm performance using an instrumental variable based on work in chapter 1 that captures the sensitivity of power reliability to weather-induced variability in river flow given that hydropower plays the key role in the economy. Progressive power policies are required as businesses, which become more dependent on electricity, are shown to be more vulnerable to power disruptions. The third chapter provides evidence that senatorial voting pattern for environmental issues in the US is responsive to natural disasters although the reactions tend to be slow, short-lived and not unidirectional. The preference for environmental stringency increases after human losses but falls after economic damages.

*In Loving Memory Of*

*My Grandparents*

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*Who Offered me the Very First Lessons of Sciences*

*which are full of Love, Hope and Encouragement.*

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# Introduction

One feature that makes human beings so special and distinctive from any other living creatures on the Earth is that their interactions with the environment are so comprehensive and complicated. Yet similar to other animals, humans receive from the environment essential elements for their survivals such as habitat, air, water, and food. Moreover, their superiority to others means that they are the only one on the planet able to organise economic activities to exploit and alter the environment at a larger and larger scale and increasingly advanced ways to satisfy their seemingly endless needs which have been growing over time in both variety and sophistication.

Indeed, it is hardly possible to imagine any activity of our modern economy that does not have consequences for the environment. All economic activity means the consumption of limited natural resources, intervention in the ecosystem or the release of pollutants to the land, water bodies or the air. The development of our increasingly populated society is also linked to the degradation of the environment such as deforestation, natural resources exhaustion, loss of biodiversity, and climate change. Fortunately, humans are also gifted with other important distinctive competencies, the ability to be self-conscious, to foresee the consequences of our activities and to prevent ourselves from causing bad outcomes. Yet, there have been always numerous opportunities for our society to contribute to the sustainability of the planet by saving natural resources, minimising the pollutants and their impacts, and restoring ecosystems. However, on many occasions, they are not translated into actions because of competition from other short-sighted interests and the lack of political determination.

The missed opportunities could be costly as the deterioration of the environment, poses many serious challenges to our society. As human activities, since the rise of the Anthropocene era, have driven the environment to move beyond the boundaries of its stasis, the Earth is likely to become less favourable for humanity than it has been for the past 10,000 years of the Holocene (Rockström *et al.*, 2009*a*,*b*).[1] Most evidently, climate change is proving to be a serious threat to the global economy in particular and development in general, and could be deterred by collective actions only (Stern, 2006; IPCC, 2014). One consequence of the changing climate is that extreme weather or climate events and the related disasters tend to be more frequent and damaging (IPCC, 2012). This carries important implications for economic activities and political decision making.

This thesis is dedicated to the investigation of aspects of the interrelationships between social processes and their interactions with natural processes. More specifically, it is comprised of three essays presented in three chapters that examine contemporary interdisciplinary issues and shed light on the relationship between environment, economics and politics. The two first essays look at the energy sector in Vietnam, a fast growing developing economy that is vulnerable to the changing climate. The sector engages in the use of natural resources on a massive scale to produce the fuel for the whole economy. In addition, as the sector is capital intensive and critical to national security, it requires huge investment and political involvement. Under such a setup, energy policies need to be considered carefully as they have important implications for both the economy and the environment. Yet it is challenging to meet the urgent need for energy to cope with rapid growth while maintaining a sustainability development path. The third essay studies the environmental legislation in a developed country (the US), and the role played by natural disasters. The chapter explores the political response to the signal given by a perception of a deteriorating environment when it is up against economic interests. A version of the first

[1] The authors propose the concept of planetary boundaries, the interlinked biophysical thresholds that should not be crossed so that the Earth system remains safe for the operation of humanity. Out of nine boundaries, three are estimated to be already transgressed, namely climate change, rate of biodiversity loss and nitrogen cycle. Other boundaries are phosphorus cycle (part of a boundary with the nitrogen cycle), stratospheric ozone depletion, ocean acidification, global freshwater use, change in land use, atmospheric aerosol loading (not determined yet), chemical pollution (not determined yet)

chapter is published in the Journal of Hydrology (Nguyen-Tien *et al.*, 2018) while the others two chapters are being prepared for submission to established journals.

The interdisciplinary nature of these three chapters means that this thesis uses a variety of data such as topography, hydrography, land cover, soil, weather, electric generation (chapter 1), firm performance, power distribution and transmission (chapter 2), legislation, demography, macro-economy, and natural disasters (chapter 3). In terms of methodology, econometrics (Ordinary Least Squares [OLS], Two-Stage Least Squares [2SLS], Fixed effects [FE], and Generalized method of moments [GMM] estimation) plays a dominant role throughout the thesis in order to identify the correlations, and where possible, the causality between the variables of interest. At the same time, methods and toolsets of different science branches are also incorporated into this thesis such as rainfall-runoff model (chapter 1), weather data interpolation and transformation (chapter 2), extreme value theory [EVT] (chapter 3) and the extensive applications of geographic information system [GIS] (throughout the thesis).

In detail, chapter 1 studies the sensitivity to weather factors, the flood control benefit and the relevance of the location of large hydropower dams across Vietnam, which provides an excellent example for a developing country reforming its socio-economy, and energy system.[2] The country is evaluated as "one of the best-performing economies in the world over the past decade" (WB, 2011) with per capita GDP growth since 1990 "among the fastest in the world, surpassed only by China" (WB and MPI, 2016). It also achieved remarkable progress in poverty alleviation with poverty rate rapidly falling from 58% in 1993 to 15.9% in 2006 (Carew-Reid *et al.*, 2010) while the proportion of households with access to electricity has risen substantially from under 2.5 percent in 1975 to 96 percent by 2009, comparable to higher average income countries like China or Thailand (Min and Gaba, 2014). ADB (2011) gives several reasons for Vietnam's success in electrification, as follows:

*'It has been stated that the challenge of energy access is not a matter of technical know-*

[2] A socio-economic reform called 'Doi moi' (renovation) started in 1986. A reform in power sector begun later, in 1995.

*how, but one of making access a priority in both the political and developmental agendas.[...] Specifically, the establishment of a strong national policy on rural electrification, coupled with an empowered national institution to head the electrification drive allowed Viet Nam to take advantage of its natural hydropower resources and create the infrastructure that allowed this source of electricity to flow, first to its base of farmers and industry, and then into every community.'*

Indeed, behind such a story of success, there is a role for hydropower dams. For many years, the construction of large dams in Vietnam since 1954, which typically requires huge amount of labour over many years with considerable financial and technical aid from international friends, was seen as a political achievement, and an icon of human's willingness to conquer nature to support the industrialisation, modernisation, and globalisation (Le and Dao, 2016). As Vietnam is abundant in water resources and has a diversity of terrain and climatic conditions, it is vulnerable to extreme weather events such as floods and droughts, and hence these dams are an important infrastructure that delivers multiple socio-economic benefits (Chairman of VNA, 2013). First, they provide a means to produce electricity on a large scale at a low price and with relatively less emissions into the environment. Therefore, hydropower represents a strategic component of the national energy mix to foster growth and combat poverty. Second, large reservoirs attached to dams are an important tool to manage water resources, protect the downstream people from flooding, and provide water for irrigation in times of drought, supporting agriculture among other economic activities. Yet hydropower in Vietnam is subject to criticism for local socio-environmental problems such as flooding downstream, deforestation, resettlement challenges and involuntary displacement (Dao, 2011; Bui and Schreinemachers, 2011; Singer *et al.*, 2014). However, if Vietnam had not built such an extensive hydropower scheme, it would arguably have not been so successful in universal electrification, poverty alleviation and economic development.

Given the importance of hydropower dams, it is worth appraising the robustness of the system and the appropriateness of their location and operational coordination. In this chapter, we extend the framework by Cole *et al.* (2014), which integrates a rainfall runoff model (GeoSFM) and regression analysis, to assess the performance of large hydropower dams, capturing their sensitivity to weather factors, their multiple purposes and their interconnectivity. The contribution is twofold. First, we use a more advanced rainfall runoff model (SWAT) coupled with datasets of higher resolution such as HydroSHEDS/HydroBASINS.[3] Second, improved data and modelling enables us to conduct a more detailed analysis, including the investigation of the cascade design (i.e., how well upstream dams support the operation of downstream dams). The contribution of the chapter is to bridge two strands of literature: regression-based hydropower system assessment (Gebretsadik *et al.*, 2012; Cole *et al.*, 2014) and SWAT application in modelling Vietnamese watershed (Rossi *et al.*, 2009; Phan *et al.*, 2011; Vu *et al.*, 2012; Wang and Ishidaira, 2012; Ho *et al.*, 2013; T.Piman *et al.*, 2013; Giang *et al.*, 2014; Wild and Loucks, 2014; Tram *et al.*, 2014; Quyen *et al.*, 2014; Khoi and Suetsugi, 2014; Le and Sharif, 2015; Vu *et al.*, 2015; Ngo *et al.*, 2015; Shrestha *et al.*, 2016).

The main results of the chapter can be summarised as follows. First, river flows simulated from a trans-boundary watershed of 977,964 km$^2$, which is delineated to 7,887 sub-basins and 53,024 Hydrological Response Units (HRUs), are shown to be a good proxy for inflows into 40 large hydropower dams between 1995-mid 2014. The use of such a proxy in energy regression models is able to explain up to 87.7% of the variation in monthly power generation. The multiple functions of large dams are captured by the estimate that they sacrifice on average 18.2% of their contemporaneous production for the purpose of flood control. This evidence may support the argument that large dams in Vietnam do not solely pursue economic interests but are also well regulated to protect those downstream. In addition, our assessment highlights the synergies created by the cascade setup such that each MWh/day increase in upstream generation adds 0.146 MWh/day to downstream generation. This evidence may suggest an overall efficient location and coordination of the dam system, which is designed to be adaptive to ex-

[3]The Geospatial Stream Flow Model (GeoSFM) and Soil and Water Assessment Tool (SWAT) are a semi distributed, physically based catchment scale hydrological models funded and supported by various agencies of the US governments (see Chapter 1 for more details). The latter is more well- developed and becomes 'one of the most widely used water quality watershed and river basin–scale models and is applied extensively to a broad range of hydrologic and/or environmental problems' (Gassman *et al.*, 2014, p. 1).

treme weather under the increasingly unfavorable conditions caused by climate change. More specifically, upstream dams store water during floods and release water during droughts, which in both cases improves the efficiency of downstream plants. However, more detailed analysis identifies several basins where the harmonisation could be improved.

While chapter 1 highlights Vietnam's success in exploiting hydropower potential to provide inexpensive electricity for its entire population among other benefits, chapter 2 raises a concern about power reliability. Indeed, power quality is still an area for improvement as Vietnam is currently ranked 113/144 countries by the Global Competitiveness Index 2012-14 (Cattelaens *et al.*, 2015). This chapter aims to quantify the impacts of power outages on firm performance and as a such, it contributes to a strand of literature that examines firms' responses to power provision (Reinikka and Svensson, 2002; Adenikinju, 2003; Alby and Dethier, 2013; Dang *et al.*, 2013; Alam, 2013; Fisher-Vanden *et al.*, 2015; Allcott *et al.*, 2016; Mensah, 2016; Grainger and Zhang, 2017) and a broader one that studies the relationship between infrastructure and development (Lee *et al.*, 1999; Davis *et al.*, 2001; Esfahani and Ramırez, 2003; Holl, 2004; Calderón and Servén, 2004; Canning and Pedroni, 2008; Baisa *et al.*, 2010; Iimi, 2011; McRae, 2015). As indicated in the literature, endogeneity concerns could be serious when attempting to quantify the losses in firm performance caused by power unreliability due to measurement errors, potential reverse causality (i.e., better- performing firms are given priority in power supply when blackout occurs) and the existence of underlying factors that may determine both power provision and firm performance (such as local economic growth or institutional quality).

The solution used in the chapter is to employ a hydro-instrumental strategy similar to Allcott *et al.* (2016); Mensah (2016); Cole *et al.* (2018). Intuitively, when an economy is highly dependent in hydropower, its power supply is unavoidably sensitive to the variability in weather factors such as rainfalls and temperature, which determine water availability in hydropower reservoirs. Under such circumstances, the weather-induced variations in river flows into large dams may well predict power provision while there is little reason for them to correlate with firm performance via other channels. Therefore, they fit to serve as an instrument for a 2SLS estimate, which is arguably more consistent than a naive OLS estimate. The approach is relevant to Vietnam as hydropower plays the leading role in the national power mix (account for 37.6% to 40.2% installed capacity), however some modifications to the methods used in the existing literature are needed. Existing studies are based on multiple grids (i.e., different countries or different states in a large country use different grids), in which the hydro-instrument is calculated for each power grid then matched with firms to explain the variation in power provision. In the case of Vietnam, we need to deal with a single grid case (i.e., all firms are connected to a same centrally-managed grid) with limited information on the power distribution.

Such a difficulty motivates our methodological contribution. First, we utilise the SWAT model to simulate river flows and the hydropower generation regression in chapter 1 to predict the power generation and the hydro-plant factors (i.e., the percentage of the designed capacity that dams may operate given the flows determined by weather conditions) for each dam. Then the predicted plant factors are weighted to compute a hydro-index showing that water availability at a nearer and larger dam has a greater impact on the power provision at a given economic centre (province). The uncertainty in the transmission and distribution rule is captured by a distance penalty parameter calibrated by the'reduced-form equation' of the 2SLS estimation. Finally, the index serves as a single instrument for power outages measured in multiple dimensions (frequency, intensity and volume) in the 'structural equation' to resolve the endogeneity concerns.

Our instrumental estimation for the cross-sectional data from two waves of the World Bank Enterprises Surveys (WBES) suggests that the negative impact of power unreliability is small and insignificant in the 2005 Survey but is considerable and significant in the 2015 Survey. One explanation is that electricity has become increasingly essential for businesses. For the later, it is estimated that a small reduction in power interruption of 22.8 minutes per year would increase the revenues of Vietnam's firms by 4.66 billion USD. Compared with their counterparts, firms supplied with less reliable power are found to have lower productivity, and to use less flexible input factors, which are not offset by more use of costly backup electricity generators.

In addition, frequent blackouts are found to cause larger damages than long-lasting blackouts.

Though our econometric model in this chapter confirms the link between weather variability and power outages via the reliance on hydropower (the 'reduced form equation'), and their consequences on firm performance (the 'structural equation'), it does not imply that Vietnam should not continue to see clean power as a source of economic growth. The chapter rather suggests that policy makers may need to seriously take into account the changes in the sensitivity of the economy to power quality. There are several approaches to enhance the reliability of the system. The first is the installation of new power sources with a focus on the sources with high reliability to fill in the gap between demand and supply. Given the fast growth of power demand, this approach, however, requires substantial investment, which could be beyond the ability of the government if the market liberalisation is not properly adopted.[4] In addition, this approach may encourage the emissions of greenhouse gas and lead to more consequences on the environment (Ha-Duong *et al.*, 2016). The second approach is to regulate the demand and enhance the efficiency of power usage. This approach is backed by the fact that power tariff in Vietnam is low in comparison with other regional countries and its electricity-GDP intensity is too high.[5] [6] While a review of the power tariff may be desirable to discourage the inefficient use of power and generate resources for the upgrade and extension of the system, care should be taken not to squeeze the vulnerable residents and reverse the poverty reduction achievements. The promotion of power-saving technology could be an effective win-win solution for both the economy and the environment. Danish Energy Agency (2017) estimates that by 2030 Vietnam potentially could save 17% electricity if appropriate energy efficiency polices are introduced.

[4]Maweni and Bisbey (2016) estimate that there is a need for annual investment by 7.5 billion USD to match the expected double energy demand between 2014- 2020, which is far beyond the historical level, for example 2.6 billion USD in 2012. Consequently, the dominant role of the state in power investment is no longer valid given that its financial capability is limited, especially amid a high debt ratio.

[5]A comparison by ADB (2015) shows that among ASEAN countries, Vietnam's electricity tariff for industry in 2011 was 5.31 US cent, the second cheapest only after the outlier Brunei (1.91 US cent) and much lower than the others: Myanmar (6.17 cent), Laos (6.785 cent), Indonesia (7.76 cent), Thailand (9.05 cent), Malaysia (9.355 cent), Cambodia (13.17 cent) and Singapore (14.5 cent).

[6]During 1990-2010, Vietnam's electricity-GDP intensity is about 1.9, while the average of the world is about 1.0. For more comparisons, the elasticity of Thailand over the same period is about 1.5 and the one of Great Britain is roughly 0.4 (Maweni and Bisbey, 2016).

In the third chapter we look at politics in a the US. In the literature, it is still unsettled whether elected politicians under an established democracy act in line with the interests of their electorate (Anderson and Mizak, 2006; Tanger *et al.*, 2011; Chupp, 2011; Canes-Wrone *et al.*, 2011; Miler, 2016; Vandeweerdt *et al.*, 2016) or are just loyal to their own ideologies (Poole and Rosenthal, 1985; Arnold, 1990; Lee *et al.*, 2004; Ringquist and Dasse, 2004; Clinton, 2006; Poole and Rosenthal, 2007). We contribute to the literature of electoral accountability by investigating the interaction between environmental legislation and natural disasters.

Despite the high development level that the US has achieved, it is still vulnerable to natural disasters. Over the period 1960-2015, natural hazards each year cost the US on average 15.2 billion dollars (at 2015 price), kill 778, and injure 4,338 people (Hazards & Vulnerability Research Institute, 2015*a*).[7] As extreme events seemingly become more common and intense possibly as a result of climate change, their costs and impact will be more significant (Walsh *et al.*, 2014). The Office of Management and Budget and the Council of Economic Advisers estimate that climate change will raise the recurring cost of four federal programs, including wildland fire suppression, crop insurance, air quality-health care, and coastal disaster relief, by $12 billion to $35 billion per year by mid-century and by $34 billion to $112 billion per year by late-century (US Government Accountability Office, 2017).

The unanticipated and devastating damages that natural disasters may cause mean that these events have an important influence on politics. For example, the occurrences of these adverse events could lead to incumbent politicians punished by voters (Abney and Hill, 1966; Achen and Bartels, 2004; Malhotra and Kuo, 2008; Healy and Malhotra, 2009; Gasper and Reeves, 2011; Bechtel and Hainmueller, 2011). For law making, natural disasters could attract media coverage and public attention and thus alter the balance of competing advocate groups and affect the decision made by elected legislators (Kahn, 2007; Birkland, 2016). Environmental legislation could be particularly sensitive for several reasons. First, since natural disasters could trigger environ-

[7] Hurricane, flooding and severe weather are the most economically damaging, incurring a cost of 267, 169, and 137 billion dollars (at 2015 price) respectively over the whole period. Meanwhile the 5 most deadly hazards are severe weather, drought & heat, winter weather, tornado, and flooding, which jointly account for 88% of fatalities.

mental disasters such as ecosystem destruction, oil spills, contaminant mobilisation, amongst many other aspects (Labadie, 2006; Atkin, 2017; Dart *et al.*, 2018; Natter and Calkins, 2018) and environmental degradation increases the vulnerability of communities to natural disasters (UNEP, 2007; Gupta and Nair, 2012; Wouter Botzen and Van Den Bergh, 2012; Estrada *et al.*, 2015), environmental regulations should be expected to be tightened if there is an increase in natural disasters. Alternatively, if economic recovery and redevelopment are put at the centre of political agenda after a natural disaster, elected legislators may dislike stringent environmental policies if think they could further squeeze businesses and negatively affect employments. The competition of these two channels means that how environmental legislation responds to natural disasters is an interesting empirical question, but to the best of our knowledge, is still left under-explored.

Our third chapter attempts to fill in the gap by combining roll call vote data at the Senate (Scorecard by League of Conservation Voters (2018)) and natural disasters at the state level (SHELDUS by Hazards & Vulnerability Research Institute (2015*b*)). A prominent contribution in term of methodology is our use of extreme value theory (EVT) and peak over thresholds (POT) model to take into account the 'fat tail' distribution of economic and human damages by natural disasters and homogenize their rarity across time and state. Our panel estimation over 44 years suggests that senators show significant responses to natural disasters at their constituency after two years of their occurrence. More specifically, their preference for stringent environmental regulation is improved after extreme human losses but reduced if economic damages are substantial and such an effect lasts for one year on average. These competing effects may help explain why attitude toward environment of politicians on some cases seems to be unresponsive to simultaneous enormous damages in both human and monetary terms of natural disasters and sticks to their ideology. A leading example is the position of President Trump on climate change reported unchanged after Hurricanes Irma and Harvey (Abramson, 2017), which is consistent with the continuation of policies less friendly to environment adopted by his Administration.

# References


Abney, F. G. and Hill, L. B. (1966), 'Natural Disasters as a Political Variable: The Effect of a Hurricane on an Urban Election', *The American Political Science Review* **60**(4), 974–981.

Abramson, A. (2017), 'No, Trump Still Hasn't Changed His Mind About Climate Change After Hurricane Irma and Harvey', pp. 2017–2019.
**URL:** *https://goo.gl/ceDPAZ*

Achen, C. H. and Bartels, L. M. (2004), 'Blind Retrospection. Electoral Responses to Drought, Flu, and Shark Attacks', *Estudio/Working Papers (Centro de Estudios Avanzados en Ciencias Sociales)* (199), 1.
**URL:** *http://www.march.es/ceacs/publicaciones/working/archivos/2004_199.pdf*

ADB (2011), Energy for all: Viet nam's success in increasing access to energy through rural electrification, Report, Asian Development Bank.
**URL:** *https://think-asia.org/bitstream/handle/11540/963/rural-electrification-vie.pdf?sequence=1*

ADB (2015), Assessment of power sector reforms in viet nam - country report, Report, Asian Developement Bank.
**URL:** *https://www.adb.org/sites/default/files/institutional-document/173769/vie-power-sector-reforms.pdf*

Adenikinju, A. F. (2003), 'Electric infrastructure failures in Nigeria: a survey-based analysis of the costs and adjustment responses', *Energy Policy* **31**(14), 1519–1530.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0301421502002082*

Alam, M. (2013), 'Coping with blackouts: Power outages and firm choices'.

Alby, P. and Dethier, J.-J. (2013), 'Firms Operating under Electricity Constraints in Developing Countries', *World Bank Economic Review* **27**(1), 109–132.
**URL:** *https://elibrary.worldbank.org/doi/abs/10.1093/wber/lhs018*

Allcott, H., Collard-Wexler, A. and O'Connell, S. D. (2016), 'How do electricity shortages affect industry? evidence from india', *American Economic Review* **106**(3), 587–624.
**URL:** *http://www.aeaweb.org/articles?id=10.1257/aer.20140389*

Anderson, W. L. and Mizak, D. A. (2006), 'Politics of environmental law: Political ideology, elitism or urban-rural interests?', *Public Choice* **129**(1-2), 131–157.

Arnold, R. D. (1990), *The Logic of Congressional Action*, Yale University Press.
**URL:** *http://www.jstor.org/stable/j.ctt32bm5b*

Atkin, E. (2017), 'Hurricane Harvey Could Also Be a Major Pollution Disaster | New Republic'.
**URL:** *https://newrepublic.com/article/144513/hurricane-harvey-also-major-pollution-disaster*

Baisa, B., Davis, L. W., Salant, S. W. and Wilcox, W. (2010), 'The welfare costs of unreliable water service', *Journal of Development Economics* **92**(1), 1–12.

Bechtel, M. M. and Hainmueller, J. (2011), 'How Lasting Is Voter Gratitude? An Analysis of the Short- and Long-Term Electoral Returns to Beneficial Policy', *American Journal of Political Science* **55**(4), 852–868.

Birkland, T. A. (2016), 'Policy Process Theory and Natural Hazards', **1**(May 2018), 1–26.
**URL:** *http://naturalhazardscience.oxfordre.com/view/10.1093/acrefore/9780199389407.001.0001/acrefore-9780199389407-e-75*

Bui, T. M. H. and Schreinemachers, P. (2011), 'Resettling farm households in northwestern vietnam: Livelihood change and adaptation', *International Journal of Water Resources Development* **27**(4), 769–785.

Calderón, C. and Servén, L. (2004), *The Effects of Infrastructure Development on Growth and Income Distribution*, Policy Research Working Papers, The World Bank.
**URL:** *https://doi.org/10.1596/1813-9450-3400*

Canes-Wrone, B., Minozzi, W. and Reveley, J. B. (2011), ‘Issue accountability and the mass public’, *Legislative Studies Quarterly* **36**(1), 5–35.

Canning, D. and Pedroni, P. (2008), ‘Infrastructure, long-run economic growth and causality tests for cointegrated panels’, *The Manchester School* **76**(5), 504–527.
**URL:** *http://dx.doi.org/10.1111/j.1467-9957.2008.01073.x*

Carew-Reid, Jeremy, Kempinski, J. and Clausen, A. (2010), Biodiversity and development of the hydropower sector: Lessons from the vietnamese experience - volume i: Review of the effects of hydropower development on biodiversity in vietnam, Report, ICEM – International Centre for Environmental Management, Prepared for the Critical Ecosystem Partnership Fund.

Cattelaens, P., Limbacher, E.-L., Reinke, F., Stegmueller, F. F. and Brohm, R. (2015), Overview of the Vietnamese Power Market – A Renewable Energy Perspective, Report, GIZ Viet Nam Energy Support Programme.

Chairman of VNA (2013), ‘Resolution of vietnam national assembly [vna] no 62/2013/qh13 on improvement in management of planning, construction investment and operation of hydropower projects’.

Chupp, B. A. (2011), ‘Environmental Constituent Interest, Green Electricity Policies, and Legislative Voting’, *Journal of Environmental Economics and Management* **62**(2), 254–266.
**URL:** *http://dx.doi.org/10.1016/j.jeem.2011.03.008*

Clinton, J. D. (2006), ‘Representation in congress: Constituents and roll calls in the 106th House’, *Journal of Politics* **68**(2), 397–409.

Cole, M. A., Elliott, R. J., Occhiali, G. and Strobl, E. (2018), ‘Power outages and firm performance in sub-saharan africa’, *Journal of Development Economics* **134**, 150 – 159.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0304387818305054*

Cole, M., Elliott, R. and Strobl, E. (2014), 'Climate change, hydro-dependency, and the african dam boom', *World Development* **60**, 84.

Dang, V., Do, T., Nguyen, C., Phung, T. and Phung, T. (2013), Economic development, inequality and climate change in vietnam, Report, Munich Personal RePEc Archive.
**URL:** *http://mpra.ub.uni-muenchen.de/54190/*

Danish Energy Agency (2017), Vietnam Energy Outlook Report 2017, Report, Danish Energy Agency.

Dao, N. (2011), 'Damming rivers in vietnam: A lesson learned in the tay bac region', *Journal of Vietnamese Studies* **6**(2), 106–140.

Dart, T., Carroll, R. and Lartey, J. (2018), 'Explosions at flooded Texas chemical plant leave confusion over toxic risk', *The Guardian* .
**URL:** *https://www.theguardian.com/us-news/2017/aug/31/explosions-flooded-texas-chemical-plant-arkema-crosby*

Davis, J., Kang, A., Vincent, J. and Whittington, D. (2001), 'How Important is Improved Water Infrastructure to Microenterprises? Evidence from Uganda', *World Development* **29**(10), 1753–1767.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0305750X01000596*

Esfahani, H. S. and Ramırez, M. T. (2003), 'Institutions, infrastructure, and economic growth', *Journal of Development Economics* **70**(2), 443–477.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0304387802001050*

Estrada, F., Botzen, W. J. W. and Tol, R. S. J. (2015), 'Economic losses from US hurricanes consistent with an influence from climate change', *Nature Geoscience* **8**, 880.
**URL:** *http://dx.doi.org/10.1038/ngeo2560 http://10.0.4.14/ngeo2560 https://www.nature.com/articles/ngeo2560#supplementary-information*

Fisher-Vanden, K., Mansur, E. T. and Wang, Q. (2015), 'Electricity shortages and firm productivity: Evidence from china's industrial firms', *Journal of Development Economics* **114**, 172–188.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0304387815000048*

Gasper, J. T. and Reeves, A. (2011), 'Make It Rain? Retrospection and the Attentive Electorate in the Context of Natural Disasters', *American Journal of Political Science* **55**(2), 340–355.

Gassman, P. W., Sadeghi, A. M. and Srinivasan, R. (2014), 'Applications of the SWAT model special section: Overview and insights', *J Environ Qual* **43**(1), 1–8.
**URL:** *http://www.ncbi.nlm.nih.gov/pubmed/25602534*

Gebretsadik, Y., Fant, C. and Strzepek, K. (2012), Impact of climate change on irrigation, crops and hydropower in vietnam, Report, UNU-WIDER.

Giang, P. Q., Toshiki, K., Sakata, M., Kunikane, S. and Vinh, T. Q. (2014), 'Modelling climate change impacts on the seasonality of water resources in the upper ca river watershed in southeast asia', *ScientificWorldJournal* **2014**, 279135.
**URL:** *https://www.ncbi.nlm.nih.gov/pubmed/25243206 https://www.ncbi.nlm.nih.gov/pmc/articles/PMC41*
*279135.pdf*

Grainger, C. A. and Zhang, F. (2017), The impact of electricity shortages on firm productivity : evidence from Pakistan, Report, World Bank Group.
**URL:** *http://documents.worldbank.org/curated/en/978661498756334535/The-impact-of-electricity-shortages-on-firm-productivity-evidence-from-Pakistan*

Gupta, A. K. and Nair, S. S. (2012), Environmental Legislation for Disaster Risk Management, Module-I.
**URL:** *http://www.preventionweb.net/files/30127_30127legal1.pdf*

Ha-Duong, M., Truong, A. H., Nguyen, H. N. and Nguyen Trinh, H. A. (2016), Synthesis Report on Socio-environmental Impacts of Coal and Coal-fired Power Plants in Vietnam,

Technical report, Vietnam Sustainable Energy Alliance.
**URL:** *https://hal-enpc.archives-ouvertes.fr/hal-01441680*

Hazards & Vulnerability Research Institute (2015*a*), '1960-2015 U.S. Hazard Losses', p. 2.
**URL:** *http://hvri.geog.sc.edu/SHELDUS/docs/Summary_1960_2014.pdf*

Hazards & Vulnerability Research Institute (2015*b*), 'Spatial Hazard Events and Losses Database for the United States, Version 14.0. [Online Database].'.
**URL:** *http://hvri.geog.sc.edu/SHELDUS/index.cfm?page=metadata*

Healy, A. and Malhotra, N. (2009), 'Myopic voters and natural disaster policy', *American Political Science Review* **103**(3), 387–406.

Ho, Q. B., Nguyen, H. Q. and Vo, L. P. (2013), 'Impacts of climage change on catchment flows and assessing its impacts on hydropower in vietnam's central highland region', *Global Perspectives on Geography* **1**(1).

Holl, A. (2004), 'Manufacturing location and impacts of road transport infrastructure: empirical evidence from Spain', *Regional Science and Urban Economics* **34**(3), 341–363.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0166046203000590*

Iimi, A. (2011), 'Effects of improving infrastructure quality on business costs: Evidence from firm-level data in Eastern Europe and Central Asia', *The Developing Economies* **49**(2), 121–147.
**URL:** *http://dx.doi.org/10.1111/j.1746-1049.2011.00126.x*

IPCC (2012), Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation, *in* C. Field, V. Barros, T. Stocker, D. Qin, D. Dokken, K. Ebi, M. Mastrandrea, K. Mach, G.-K. Plattner, S. Allen, M. Tignor and P. Midgley, eds, 'A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change', Cambridge University Press, Cambridge, UK, and New York, NY, USA.
**URL:** *http://ebooks.cambridge.org/ref/id/CBO9781139177245*

IPCC (2014), ‘Summary Chapter for Policymakers’, *Climate Change 2014 Synthesis Report* .

Kahn, M. E. (2007), ‘Environmental disasters as risk regulation catalysts? The role of Bhopal, Chernobyl, Exxon Valdez, Love Canal, and Three Mile Island in shaping U.S. environmental law’, *Journal of Risk and Uncertainty* **35**(1), 17–43.

Khoi, D. N. and Suetsugi, T. (2014), ‘The responses of hydrological processes and sediment yield to land-use and climate change in the be river catchment, vietnam’, *Hydrological Processes* **28**(3), 640–652.
**URL:** *http://onlinelibrary.wiley.com/store/10.1002/hyp.9620/asset/hyp9620.pdf?v=1&t=ix0o7jx9&s=a1c1*

Labadie, J. R. (2006), Environmental Management and Disasters : Contributions of the Discipline to the Profession and Practice of Emergency Management, *in* D. A. McEntire, ed., ‘Disciplines, Disasters and Emergency Management: The Convergence and Divergence of Concepts, Issues and Trends from the Research Literature’, FEMA Emergency Management Institute, chapter 20, pp. 260–271.
**URL:** *https://training.fema.gov/hiedu/aemrc/booksdownload/ddemtextbook/*

Le, A. T. and Dao, T. V. N. (2016), *Hydropower developement in Vietnam: Challenges and solutions*, Science and Technology Publisher, Ha Noi, Vietnam.

Le, T. B. and Sharif, H. O. (2015), ‘Modeling the projected changes of river flow in central vietnam under different climate change scenarios’, *Water (Switzerland)* **7**(7), 3579–3598.

League of Conservation Voters (2018), ‘National Environmental Scorecard’.
**URL:** *http://scorecard.lcv.org/scorecard?year=all*

Lee, D. S., Moretti, E. and Butler, M. J. (2004), ‘Do Voters Affect or Elect Policies? Evidence from the U. S. House’, *The Quarterly Journal of Economics* **119**(3), 807–859.
**URL:** *https://academic.oup.com/qje/article-lookup/doi/10.1162/0033553041502153*

Lee, K. S., Anas, A. and Oh, G.-T. (1999), ‘Costs of Infrastructure Deficiencies for Manufac-

turing in Nigerian, Indonesian and Thai Cities', *Urban Studies* **36**(12), 2135–2149.
**URL:** *http://www.jstor.org/stable/43084411*

Malhotra, N. and Kuo, A. G. (2008), 'Attributing blame: The public's response to Hurricane Katrina', *Journal of Politics* **70**(1), 120–135.

Maweni, J. J. and Bisbey, J. (2016), A financial recovery plan for Vietnam Electricity (EVN) : with implications for Vietnam's power sector., Report, World Bank Group,.
**URL:** *http://documents.worldbank.org/curated/en/971901468196178656/A-financial-recovery-plan-for-Vietnam-Electricity-EVN-with-implications-for-Vietnam-s-power-sector*

McRae, S. (2015), 'Infrastructure Quality and the Subsidy Trap', *American Economic Review* **105**(1), 35–66.
**URL:** *http://www.aeaweb.org/articles?id=10.1257/aer.20110572*

Mensah, J. T. (2016), Bring back our light: Power outages and industrial performance in sub-saharan africa, Report.

Miler, K. (2016), 'Legislative Responsiveness to Constituency Change', *American Politics Research* **44**(5), 816–843.

Min, B. and Gaba, K. (2014), 'Tracking electrification in vietnam using nighttime lights', *Remote Sensing* **6**(10), 9511.
**URL:** *http://www.mdpi.com/2072-4292/6/10/9511*

Natter, A. and Calkins, L. B. (2018), 'Harvey Responders Say the Arkema Plant Blaze Made Them Sick', *Bloomberg* .
**URL:** *https://www.bloomberg.com/news/articles/2017-09-07/harvey-responders-say-they-were-sickened-by-arkema-plant-blaze*

Ngo, T. S., Nguyen, D. B. and Rajendra, P. S. (2015), 'Effect of land use change on runoff and sediment yield in da river basin of hoa binh province, northwest vietnam', *Journal of Mountain Science* **12**(4), 1051–1064.

Nguyen-Tien, V., Elliott, R. J. R. and Strobl, E. A. (2018), 'Hydropower generation, flood control and dam cascades: A national assessment for Vietnam', *Journal of Hydrology* **560**, 109–126.

**URL:** *https://www.sciencedirect.com/science/article/pii/S0022169418301458*

Phan, D. B., Wu, C. C. and Hsieh, S. C. (2011), 'Impact of climate change on stream discharge and sediment yield in northern viet nam', *Water Resources* **38**(6), 827–836.

**URL:** *http://download.springer.com/static/pdf/76/art%253A10.1134%252FS0097807811060133.pdf?orig*

Poole, K. T. and Rosenthal, H. (1985), 'A Spatial Model for Legislative Roll Call Analysis', *American Journal of Political Science* **29**(2), 357–384.

Poole, K. T. and Rosenthal, H. (2007), *Ideology and Congress*, Transaction Publishers.

**URL:** *https://books.google.co.uk/books/about/Ideology_and_Congress.html?id=eOuZqa7UbqUC&redir_*

Quyen, N. T. N., Liem, N. D. and Loi, N. K. (2014), 'Effect of land use change on water discharge in srepok watershed, central highland, viet nam', *International Soil and Water Conservation Research* **2**(3), 74–86.

Reinikka, R. and Svensson, J. (2002), 'Coping with poor public capital', *Journal of Development Economics* **69**(1), 51–69.

**URL:** *http://www.sciencedirect.com/science/article/pii/S0304387802000524*

Ringquist, E. J. and Dasse, C. (2004), 'Lies, damned lies, and campaign promises? Environmental legislation in the 105th congress', *Social Science Quarterly* **85**(2), 400–419.

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E. F., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., Nykvist, B., De Wit, C. A., Hughes, T., Van Der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P. K., Costanza, R., Svedin, U., Falkenmark, M., Karlberg, L., Corell, R. W., Fabry, V. J., Hansen, J., Walker, B., Liverman, D., Richardson, K., Crutzen, P. and Foley, J. A. (2009*a*), 'A safe operating space for humanity', *Nature* **461**(7263), 472–475.

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., Nykvist, B., de Wit, C. A., Hughes, T., van der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P. K., Costanza, R., Svedin, U., Falkenmark, M., Karlberg, L., Corell, R. W., Fabry, V. J., Hansen, J., Walker, B., Liverman, D., Richardson, K., Crutzen, P. and Foley, J. (2009*b*), 'Planetary boundaries: Exploring the safe operating space for humanity', *Ecology and Society* **14**(2).

Rossi, C. G., Srinivasan, R., Jirayoot, K., Duc, T. L., Souvannabouth, P., Binh, N. and Gassman, P. W. (2009), 'Hydrologic evaluation of the lower mekong river basin with the soil and water assessment tool model', *International Agricultural Engineering Journal* **18**(1-2), 1–13.

Shrestha, B., Cochrane, T. A., Caruso, B. S., Arias, M. E. and Piman, T. (2016), 'Uncertainty in flow and sediment projections due to future climate scenarios for the 3s rivers in the mekong basin', *Journal of Hydrology* **540**, 1088–1104.

Singer, J., Pham, H. T. and Hoang, H. (2014), 'Broadening stakeholder participation to improve outcomes for dam-forced resettlement in vietnam', *Water resources and rural development* **4**, 85–103.

Stern, N. (2006), 'The Economics of Climate Change', *Stern Review* .
**URL:** *http://mudancasclimaticas.cptec.inpe.br/ rmclima/pdfs/destaques/sternreview_report_complete.pdf*

Tanger, S. M., Zeng, P., Morse, W. and Laband, D. N. (2011), 'Macroeconomic conditions in the U.S. and congressional voting on environmental policy: 1970-2008', *Ecological Economics* **70**(6), 1109–1120.
**URL:** *http://dx.doi.org/10.1016/j.ecolecon.2010.12.021*

T.Piman, Cochrane, T. A., Arias, M. E., A.Green and Dat, N. (2013), 'Assessent of flow changes from hydropower developement and operations in sekong, sesan, and srepok rivers of the mekong basin', *Journal of Water Resources Planning and Management* **139**(6), 723–732.

Tram, V. N. Q., Liem, N. D. and Loi, N. K. (2014), 'Assessing water availability in poko catchment using SWAT model', *Khon Kaen Agricultural Journal* **42**(2).

UNEP (2007), *Environment and disaster risk - Emerging Perspectives*.

US Government Accountability Office (2017), Report to Congressional Requesters: Climate Change - Information on Potential Economic Effects Could Help Guide Federal Efforts to Reduce Fiscal Exposure, Technical Report September.
**URL:** *https://www.gao.gov/assets/690/687466.pdf*

Vandeweerdt, C., Kerremans, B. and Cohn, A. (2016), 'Climate voting in the US Congress: the power of public concern', *Environmental Politics* **25**(2), 268–288.
**URL:** *http://dx.doi.org/10.1080/09644016.2016.1116651*

Vu, M. T., Raghavan, S. V. and Liong, S. Y. (2012), 'SWAT use of gridded observations for simulating runoff – a vietnam river basin study', *Hydrology and Earth System Sciences* **16**(8), 2801–2811.
**URL:** *http://www.hydrol-earth-syst-sci.net/16/2801/2012/hess-16-2801-2012.pdf*

Vu, M. T., Raghavan, V. S. and Liong, S. Y. (2015), 'Ensemble climate projection for hydro-meteorological drought over a river basin in central highland, vietnam', *KSCE Journal of Civil Engineering* **19**(2), 427–433.

Walsh, J., Wuebbles, D., Hayhoe, K., Kossin, J., Kunkel, K., Stephens, G., Thorne, P., Vose, R., Wehner, M., Willis, J., Anderson, D., Doney, S., Feely, R., Hennon, P., Kharin, V., Knutson, T., Landerer, F., Lenton, T., Kennedy, J. and Somerville, R. (2014), Climate Change Impacts in the United States: The Third National Climate Assessment, Chapter 2: Our Changing Climate, *in* J. M. Melillo, T. T. Richmond and G. W. Yohe, eds, 'The Third National Climate Assessment', number October, U.S. Global Change Research Program, chapter 2, pp. 19–67.

Wang, J. and Ishidaira, H. (2012), 'Effects of climate change and human activities on streamflow and sediment flow into the hoa binh reservoir', *Journal of Japan Society of Civil Engineers* **68**(4).

WB (2011), Vulnerability, risk reduction, and adaptation to climate change vietnam, Report,

World Bank (WB).
**URL:** *http://countryadaptationprofiles.gfdrr.org*

WB and MPI (2016), Vietnam 2035 : Toward prosperity, creativity, equity, and democracy, Report, World Bank (WB) and Vietnam Misnistry of Planning and Investment (MPI).
**URL:** *http://documents.worldbank.org/curated/en/996421479825859721/pdf/103435-v2-PUBLIC.pdf*

Wild, T. B. and Loucks, D. P. (2014), 'Managing flow, sediment, and hydropower regimes in the sre pok, se san, and se kong rivers of the mekong basin', *Water Resources Research* **50**(6), 5141–5157.

Wouter Botzen, W. J. and Van Den Bergh, J. C. J. M. (2012), 'Monetary valuation of insurance against flood risk under climate change', *International Economic Review* **53**(3), 1005–1026.
**URL:** *https://doi.org/10.1111/j.1468-2354.2012.00709.x*

# Chapter 1

# Hydropower Generation, Flood Control and Dam Cascades: A National Assessment for Vietnam

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## Chapter abstract

Vietnam is a country with diverse terrain and climatic conditions and a dependency on hydropower for a significant proportion of its power needs and as such, is particularly vulnerable to changes in climate. In this paper we apply SWAT (Soil and Water Assessment Tool) derived discharge simulation results coupled with regression analysis to estimate the performance of hydropower plants for Vietnam between 1995 to mid-2014 when both power supply and demand increased rapidly. Our approach is to examine the watershed formed from three large inter-boundary basins: The Red River, the Vietnam Coast and the Lower Mekong River, which have a total area of 977,964 $km^2$. We then divide this area into 7,887 sub-basins with an average area of 131.6$km^2$ (based on level 12 of HydroSHEDS/HydroBASINS datasets) and 53,024 Hydrological Response Units (HRUs). Next we simulate river flow for the 40 largest hydropower plants across Vietnam. Our validation process demonstrates that the simulated flows are significantly correlated with the gauged inflows into these dams and are able to serve as a good proxy for the inflows into hydropower dams in our baseline energy regression, which captures 87.7% of the variation in monthly power generation In other results we estimate that large dams sacrifice on average around 18.2% of their contemporaneous production for the purpose of flood control. When we assess Vietnam's current alignment of dams we find that the current cascades of large hydropower dams appear to be reasonably efficient: each MWh/day increase in upstream generation adds 0.146 MWh/day to downstream generation. The study provides evidence for the multiple benefits of a national system of large hydropower dams using a cascade design. Such a system may help overcome future adverse impacts from changes in climate conditions. However, our results show that there is still room for improvement in the harmonization of cascades in some basins. Finally, possible adverse hydro-ecological impacts due to the proliferation of large upstream dams, including those located beyond Vietnam's border, need to be carefully considered.

"We must turn hydrological enemies into hydrological friends. The ultimate goal is to conquer the river to benefit all people. "

*Talked by President Ho Chi Minh in his boat trip on Da River (1960), where Hoa Binh (Peace), one of the largest dams in Vietnam (1,920 MW) was built later (1979-1994)*

## 1.1 Introduction

Hydropower, which utilizes running or falling water as the chief input into electricity generation, is the leading renewable source for electricity generation globally, supplying 71% of all renewable electricity. Reaching 1,064 GW of installed capacity in 2016, it generated 16.4% of the world's electricity from all sources (World Energy Council, 2017). Although attractive as a cheap, long-lasting, flexible and low-polluting renewable energy source, it is sensitive to changes in hydrology as a result of variation in weather conditions particularly rainfall and temperature (Kumar *et al.*, 2011; IFC, 2015). To assess the state of a hydropower system requires an evaluation of water availability. However, the absence of a consistent data at the country level means such an evaluation can be challenging. In many cases, measures of the inflow into a hydropower dam is not available or accessible. Modelling hydropower production is further complicated by hydrpower dams being increasingly spatially connected so that they form cascades.[1]

There is a small but growing literature that incorporates rainfall-runoff models and regression analysis to estimate the energy generation from a hydropower system conditional on weather-induced variations in river flow. Rainfall-runoff models, in conjunction with remote-sensing datasets, are one of the solutions employed to overcome the lack of consistent data on a large scale. Meanwhile, regression analysis enables the researcher to establish the relationship between water availability and power generation. Notable papers include Cole *et al.* (2014) who use the GeoSFM model and regression techniques to assess the potential risks to energy supply

[1]In addition to power production, hydropower dams typically serve multiple purposes including, but not limited to, flood control, irrigation, and navigation

in hydro-dependent African countries under different IPPC climate change scenarios.[2] Studies for Vietnam include Gebretsadik *et al.* (2012) who employ the CLIRUN-II model to simulate river flow for Vietnam in an integrated study while (Arndt *et al.*, 2015) evaluate the impact of climate change on multiple water-dependent sectors including energy in Vietnam.[3] However, these studies do not take into account the multiple purpose use of hydropower dams and the interactions between them. Indeed, a recent paper by de Faria *et al.* (2017) looking at the local socio-economic impact of large dams highlights the lack of (1) quantitative studies looking at impacts over an extended period and (2) a lack of studies that consider multiple projects in the context of a developing country.

The purpose of this paper is fill this gap in the literature and to estimate the performance of the hydropower system across the whole of Vietnam using new data and advanced regression modelling techniques. More specifically, our main contribution is to estimate the impact of water availability, flood control and the interconnected cascades of dams on hydropower production for the period 1995 to 2014. With floods being the most common natural disaster in the country and with climate change predicted to lead to more extreme weather patterns it is important that we gain a better understanding of the role of hydropower dams in both the mitigation of floods and droughts as well as providing a reliable and clean source of energy.[4] Our methodological approach allows us to answer a number of questions relevant for water resource management and Vietnam future energy strategy: (1) How is national hydropower generation affected by variations in weather and is it robust to extreme hydrological changes? (2) What is the trade-off between power generation and flood control? and (3) Is the location of large hydropower dams appropriate to enable coordination among dams through the use of dam cas-

[2]The GeoSFM model is a semi distributed, physically based catchment scale hydrological model originally developed by the National Centre for Earth Observation and Science (EROS) to support the Famine Early Warning System Network (FEWSNET) through river flow monitoring. See Cole *et al.* (2014) for more details.

[3]CLIRUN-II is the latest in a family of hydrologic models developed specifically for the analysis of the impact of climate change on river-runoff. See Gebretsadik *et al.* (2012) for details.

[4]Flooding is the most common weather-related disaster and is estimated to affect 2.3 billion people (mainly in the Asia) (CRED, 2015). In Vietnam, floods rank second among natural disasters. According to national statistics, natural disasters in Vietnam are responsible for 750 deaths annually and economic losses equivalent to 1.5% of GDP (IFAD, 2010). In October 2017 floods killed 72 people and damaged 22,000 hectares of rice with deforestation being blamed for the floods being more severe than usual (https://www.nytimes.com/reuters/2017/10/16/world/asia/16reuters-asia-storm-vietnam.html).

cades and how do cascades affect production? A second contribution is that our methodology will allow future researchers to identify how variations in weather may impact those economic activities that are dependent on electricity via variation in power supply. This source of exogenous variation is useful as it allows researchers to address a number of endogeneity concerns in studies of the relationship between firm performance and electricity provision (Allcott *et al.*, 2016; Fisher-Vanden *et al.*, 2015; Alam, 2013) or household welfare and electrification (Grogan, 2016; Khandker *et al.*, 2009; Walle *et al.*, 2013).

To model river flow we use the HydroSHEDS/HydroBASINS dataset (Lehner, 2014; Lehner *et al.*, 2008), which is derived from the detailed SRTM DEM at three arc-seconds.[5] Consequently, the river network and nested basin system created by HydroSHEDS/HydroBASINS has a higher resolution than the popular Hydro1K dataset.[6] As a result we are able to undertake our analysis at a more disaggregated spatial level which we believe is necessary if one is to accurately model dam interactions. To the best of our knowledge, we are also the first to apply the SWAT model for Vietnam at the national scale.

To model river-flow we use the SWAT (Soil and Water Assessment Tool) river-runoff model. SWAT is "one of the most widely used water quality watershed and river basin–scale models and is applied extensively to a broad range of hydrologic and/or environmental problems" (Gassman *et al.*, 2014, p. 1). SWAT is chosen for this study because it is computationally efficient and uses readily available inputs (Arnold and Fohrer, 2005) that are relevant for modelling large-scale watersheds as required in this study. Specifically, SWAT has been applied to large-scale

[5]A digital elevation model (DEM) is a digital model or 3D representation of a terrain's surface created from terrain elevation data. Source: https://en.wikipedia.org/wiki/Digital _ elevation _ model. DEM data is stored in a format that utilizes three, five, or 30 arc-seconds of longitude and latitude to register cell values. The geographic reference system treats the globe as if it were a sphere divided into 360 equal parts called degrees. An arc-second represents the distance of latitude or longitude traversed on the earth's surface while travelling one second (1/3600th of a degree). At the equator, an arc-second of longitude approximately equals an arc-second of latitude, which is 1/60th of a nautical mile (or 101.27 feet or 30.87 meters). Arc-seconds of latitude remain nearly constant, while arc-seconds of longitude decrease in a trigonometric cosine-based fashion as one moves toward the earth's poles. Source: http://www.esri.com/news/arcuser/0400/wdside.html.

[6]The Hydro1K dataset which is a comprehensive global geographic database at a resolution of 1 km that includes streams, drainage basins and ancillary layers derived from the 30 arc-second digital elevation model (DEM) of the world (GTOPO30) generated by the U.S. Geological Survey (USGS, 2015) and has been used for large scale river flow modelling by (Cole *et al.*, 2014; Gebretsadik *et al.*, 2012).

watersheds all over the world, for example China (Hao *et al.*, 2004), West Africa (Schuol and Abbaspour, 2006), and Europe (Abbaspour *et al.*, 2015). For a summary of SWAT applications for the US and EU see Arnold and Fohrer (2005).

There is also an emerging literature that applies the SWAT model to Vietnamese watersheds. For example, it has been used to study the hydrological process and sediment transport in the trans-boundary basin of Lower Mekong River (LMR), which is shared by Cambodia, Laos, Thailand, Myanmar, and Vietnam (Rossi *et al.*, 2009; Piman *et al.*, 2013). A part of the LMR, the Sesan, Srepok, and Sekong rivers (widely referred to as the 3S rivers) shared by Vietnam, Laos and Cambodia is particularly attractive to researchers because of the recent boom in hydropower (Wild and Loucks, 2014; T.Piman *et al.*, 2013; Shrestha *et al.*, 2016). There are also a series of studies that apply SWAT to separate basins in different parts of Vietnam: the North (Wang and Ishidaira, 2012; Phan *et al.*, 2011; Ngo *et al.*, 2015), the Central Coast (Giang *et al.*, 2014; Le and Sharif, 2015), the Central Highland (Vu *et al.*, 2012; Tram *et al.*, 2014; Vu *et al.*, 2015; Quyen *et al.*, 2014), and the South (Ho *et al.*, 2013; Khoi and Suetsugi, 2014). Although a frequent application of SWAT is to assess the impact of climate change on hydrological processes (Phan *et al.*, 2011; Giang *et al.*, 2014; Le and Sharif, 2015; Vu *et al.*, 2015) they have also been used to evaluate the impact of human activities that take into account deforestation (Khoi and Suetsugi, 2014), forest planting, soil protection, crop conversion (Ngo *et al.*, 2015; Quyen *et al.*, 2014), and hydropower construction and operation (Wang and Ishidaira, 2012; Le *et al.*, 2014). Although the application of these models varies they all attempt to inform policy makers on various aspects of water management, agricultural land use, and energy supply. However, none of these papers examine Vietnam at a national scale.

The remainder of this paper is organised as follows. Section 2 describes the evolution of hydropower in Vietnam. Section 3 describes our methodology and data including the materials needed for our hydrological simulation, the SWAT model, the consolidation and transformation of hydropower and the regression techniques used in the paper. We present our results in Section 4. The final section concludes.

## 1.2 Hydropower in Vietnam

Understanding the hydrology of Vietnam is important for the reasons highlighted in the introduction. Located in the south-east of the Indochinese peninsula, Vietnam's terrain is dominated by tropical hills and densely forested highlands. This means that Vietnam's lowlands, which are suitable for agricultural cultivation, cover less than 25% of its area with production concentrated in the Red River Delta (in the North) and the Cuu Long River Delta (in the South). The majority of water resources (63.9% of total flows) are concentrated in these basins while other parts of the country, that occupy more than 75% of the total area of Vietnam, receive just over 35% of the national total river-runoff. Yet Vietnam is abundant in water resources with 2,360 rivers above 10 km in length and 16 river basins above 2,500 km$^2$ in area. The annual run-off volume is around 847 km$^3$. However a population of nearly 100 million means that the total water volume per capita is still only around 9,560m$^3$ per year compared to an average of global value of 10,000m$^3$ according to the International Water Resources Association (IWRA) (MONRE, 2012).

In the future, a rapidly growing economy and continued urbanization is expected to increase pressure on water resources. In addition, Vietnam's river network is connected to neighbouring countries with 72% of its largest combined basin of about 1.167 million km$^2$ located beyond its border (MONRE, 2012). This means Vietnam's water availability could be severely affected if upstream countries were to change their demand or decide to divert or manipulate the river flow. Finally, although the monsoon tropical climate brings about a high average of annual rainfall of around 1940mm, the mountainous and hilly terrain causes a high degree of inter-annual rainfall variability. As a result, Vietnam's water availability can change dramatically throughout the year. This means that foods and prolonged droughts can occur within the same year and region. As a rule, the dry season lasts around 6 – 9 months (with exact times varying across the country) and accounts for only 20-30% of annual run-off. At the same time, half of the 15 major basins experience a shortage of water (MONRE, 2012).

Under such challenging circumstances, dams, reservoirs, and their associated irrigation systems play an important role in the water management of Vietnam. The combined total storage capacity of reservoirs across the country is about 37 billion $m^3$, which is equivalent to 4.5% of Vietnam's average annual run-off. The network of over 7,000 dams means that Vietnam is one of the most dammed in the world alongside the US and China (Pham and Pham, 2014).

Our study covers the period 1995-2014 which is a time when Vietnam experienced rapid growth in the demand for electricity. Between 1995-2005, demand for electricity grew on average by 15% per annum as a result of an economic growth rate of around 7.5% per year (Huu, 2015). At current growth rates, projections are that Vietnam's energy supply will need to triple by 2020 with additional supply coming chiefly from petroleum, coal, natural gas, and hydropower (ADB, 2015*b*). As a result, per capita energy consumption is projected to increase to 5,400 kilowatt-hours by 2030 from 985 kilowatt-hours in 2010 (ADB, 2013). As an inexpensive and available source of power, hydropower is a key component of the national energy mix. The ten major rivers suitable for hydropower construction have an approximate total potential capacity of 21,000-24,000 MW (UNIDO and ICSHP, 2013).[7] In the last two decades, Vietnam has increased construction of hydropower plants to the extent that it has exploited nearly 70% of its theoretical hydropower potential (Huu, 2015).[8] Hydropower currently contributes 44% of Vietnam's installed power capacity (ADB, 2015*a*). As part of its development plan looking ahead to 2035 (PDP7 revised) (Prime Minister, 2016), Vietnam continues to prioritise the development of hydropower, especially multi-purpose projects that combine flood control, irrigation, and electricity generation. The total capacity of hydropower plants is planned to increase from approximately 17,000 MW (2016) to 21,600 MW (2020)[9]. In addition, the pumped storage electricity plants are scheduled to have a total capacity of 1,200 MW in 2025 and 2,400 MW in 2030.[10]

[7] For comparison, the total power installed capacity of Vietnam in 2015 is 38,642 MW. Hence, if hydropower's potential was to be fully exploited it could account for 54% - 62 % of the total power installed capacity in 2015.

[8] Compared to a global average rate of 35%

[9] However, the share of hydropower in national electricity production is predicted to fall to 29.5% by 2020 and 15.5% by 2030 (due to faster growth of other components of the energy sector).

[10] Vietnam is predicted to be among the countries likely to be most affected by climate change (WB & MPI, 2016). This vulnerability has come to the attention of the government and international organizations (ADB, 2013;

## 1.3 Material and Methods

### 1.3.1 Material for Hydrological Simulation

To develop the SWAT model for Vietnam we use data generated through remote sensing. For the administrative boundary maps, we use the Global Administrative unit layers (GAUL) (version 2015), which provides "the most reliable spatial information on administrative units for all countries in the world" (FAO, 2015). Our hydrographic data comes from HydroSHEDS (Hydrological data and maps based on SHuttle Elevation Derivatives at multiple Scales) (Lehner *et al.*, 2008) and its subset HydroBASINS (Lehner and Grill, 2013). HydroSHEDS is a derivative of the digital elevation model (DEM) at a 3 arc-second resolution of the Shuttle Radar Topography Mission (SRTM). The elevation data was void-filled, hydrologically processed, and corrected to produce a consistent and comprehensive suite of geo-referenced data that enables the analysis of upstream and downstream connectivity of watersheds. Among the subsets of the HydroSHEDS database, the polygon layers that depict watershed boundaries and sub-basin delineations at a global scale critical for hydrological analysis are termed HydroBASINS. HydroBASINS delineates and codes sub-basins purely based on topographic and hydrographic bases without any local information (for example the name of rivers/ basins). To mitigate this, we utilize the basin and river layers of the dataset named "Rivers in South and East Asia" derived from HydroSHEDS by FAO (2014) which provides a river and basins network that simplifies HydroBASINS to include annotated attributes, such as the name of each large river and basin and the tentative classification of perennial and intermittent streams.

For our analysis we require a large amount of consistently collected weather data. Although Vietnam has an intensive network of meteorological stations, access to the data to such a large number of stations over a long time period is prohibitively costly. Even if access were possible,

FAO, 2011; IFAD, 2010, 2014; IMHEN, 2010; IPCC, 2007; ISPONRE, 2009; MONRE, 2003, 2009, 2010, 2011; WB, 2010, 2011; WB and MPI, 2016) with the main threats being increasing temperature, altered rainfall patterns, and rising sea levels. For hydropower, higher temperatures are thought to lead to an increase in demand for energy (MONRE, 2010) whilst also affecting stream flows into hydropower plants (WB, 2011).

inconsistencies in data availability (especially the missing data in weather series) prevents us using this data for watershed analysis on a large scale. In addition, since Vietnam shares river basins with Laos, Cambodia and China, the weather data outside of Vietnam would also be needed since variations in rainfall and temperature in the neighbouring countries could affect the discharge of downstream rivers in Vietnam. Our solution is to use a high quality gridded weather database that supports SWAT applications from the Climate Forecast System Reanalysis (CFSR) by the US's National Centers for Environmental Prediction (NCEP) (Saha *et al.*, 2010, 2014). To obtain information on soil profile, we use the Digital Soil Map of the World (DSMW) version 3.6 (FAO, 2007). The (physical and chemical) characteristics of each soil unit are tabulated by Schuol *et al.* (2008). For land cover information, we use the University of Maryland Department of Geography (UMD) Land Cover classification collection at the 1km pixel resolution (Hansen *et al.*, 1998, 2000). The resolution of materials for the simulation are summarised in Table 1.1.

**[Table 1.1 about here]**

### 1.3.2 The SWAT Hydrological Simulator

SWAT (Arnold *et al.*, 1998) is a continuation of thirty years of non-point source modelling by the US Department of Agriculture (USDA), the Agricultural Research Service (ARS), and Texas A&M University.[11] The model is a physically based, continuous, semi-distributed model that was initially developed to project the impact of land management practices on water, sediment and agricultural chemical yields in large complex catchment areas under various soil conditions, land use and management over a long time period (Neitsch *et al.*, 2009). More recently it has been incorporated into a variety of GIS interfaces such as SWAT/ GRASS (Srinivasan and Arnold, 1994), ArcView-SWAT (AVSWAT) (Di Luzio *et al.*, 2004) and ArcSWAT (Olivera

[11]Other federal agencies also contributed to the model, including the US Environmental Protection Agency, the Natural Resources Conservation Service, the National Oceanic and the Atmospheric Administration and the Bureau of Indian Affairs.

*et al.*, 2006).

SWAT enables the simulation of numerous physical and chemical processes: discharge, erosion, nutrients, pesticides and management (rotations and water use) (Neitsch *et al.*, 2009). It divides a given watershed into a number of sub-basins mainly based on topography characteristics given a chosen number or size of sub-basin. This process is typically referred to as watersheds delineation. However, each sub-basin is not treated as a lump but instead each sub-basis in broken down into different hydrologic response units (HRU) each considered as a homogenous unit with their own unique set of land cover, soil and management features. The hydrological cycle of a watershed is simulated based on two processes. First, the land phase controls the amount of water flowing to the main channel of each sub- basin and second, the routing phase controls the movement of water through the channel (river) network to an outlet of the watershed.

**The land phase** The land phase of the hydrological cycle is based on the water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^{t} \left( R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw} \right) \ (mm\ H_2O) \tag{1.1}$$

where the final soil water content ($SW_t$) is made up of the sum of initial soil water content ($SW_0$) and a daily-time-step summation of the difference between the amount of precipitation $\left(R_{day}\right)$, and the sum of the amount of surface runoff $\left(Q_{surf}\right)$, evapotranspiration $(E_a)$, percolation and bypass flow exiting the soil profile bottom $\left(w_{seep}\right)$, and return flow $\left(Q_{gw}\right)$.

Equation (1) captures potential pathways of water movement simulated by SWAT. Once precipitation descends, it is either intercepted or held in the vegetation canopy or falls to the soil surface. Water on the soil surface infiltrates into the soil profile or flows overland as runoff. Runoff moves relatively quickly toward a stream channel and contributes to a short-term stream response. Infiltrated water is either held in the soil and later evapotranspried or slowly makes its way to the surface water system via underground paths. Different crops and soils appear with varying evapotranspiration. Runoff is projected individually for each HRU then combined to obtain a total runoff for the watershed. Details about each phase can be found in Arnold *et al.* (1998); Neitsch *et al.* (2009).

**Routing phase** The lump of runoff in each sub-basin is calculated and then routed to the main channel through the stream network using either the variable storage coefficient method by Jimmy (1969) or the Muskingum routing method. The underlying principle is that water discharges downstream except for that part that is lost due to evaporation and transmission through the bed of the channel and the removal for agricultural and human use.

### 1.3.3 Hydrological Simulation

In this paper we simulate river flow for Vietnam using the ArcSWAT 10.2 interface (SWAT model incorporated in ArcGIS 10.2).

The first step is to delineate the watershed. The watershed we study is a combination of three large basins as defined by the "FAO Rivers in South and East Asia": Red River (165,007 $km^2$), Vietnam Coast (186,187 $km^2$), and a part of Mekong River (similar to Lower Mekong River with an area of 626,771 $km^2$). The total area of the watershed is 977,964 $km^2$.

Figure 1.1 shows the transboundary watershed shared by Vietnam, China, Myanmar, Lao PDR, Thailand and Cambodia. The area within Vietnam accounts for 32.22% the total area of the watershed and covers 96.15% (315,122 $km^2$/327,727 $km^2$) of Vietnam's mainland area. The remainder belongs to the Bang Giang – Ky Cung river basin, which makes no meaningful contribution to Vietnam's overall hydropower production. ArcSWAT offers two options for breaking the watersheds into smaller sub-basins: burning a river network from a DEM input or using layers that predefine sub-basins and the river network. We chose the second option to take advantage of the HydroBASINS dataset. Hence, the watershed is divided into 7,887 sub-basins at level 12 of HydroBASINS.

**[Figure 1.1 about here]**

Table 1.2 summarises the sub-basin data and shows that their areas vary from 0.2 $km^2$ to 368.6 $km^2$, with a mean of 131.6 $km^2$. The use of HydroBASINS has two advantages over using DEM. First, HydroBASINS was derived from HydroSHEDS, which already hydrographically conditioned DEM. DEM like SRTM has some characteristics, artefacts, and anomalies unfavourable for hydrologic application (Lehner, 2013).[12] Second, HydroBASINS provides two nested coding systems (Pfafstetter codes and HydroSHEDS ID). These codes are a useful for our spatial analysis as they help us to determine systematically the upstream- downstream relationship between dams. Despite using predefined basins, a DEM is still required to calculate the topography characteristics of each basin and hence we used the HydroSHEDS void-filled DEM for this purpose.

**[Table 1.2 about here]**

ArcSWAT divides each sub-basin into HRUs using a combination of soil, land use and slope layers. The soil and land use layers are listed in subsection 1.3.1. The slope layer was created by ArcSWAT using the HydroSHEDS void-filled DEM. We determined three classes of slope in line with the soil slope classification of DSMW: 0-8% (class 1), 8-30% (class 2) and above 30% (class 3), which respectively contribute 64.12%, 31.51%, and 4.37% to the area of the watershed. Based on the above layers, ArcSWAT assigned multiple HRUs to each watershed given our sensitivity thresholds (5% for land use and soil and 20% for slope). In our final data set the watershed is divided into 7,887 sub-basins and 53,024 HRUs. Daily data for each sub-basin on the maximum and minimum temperature, precipitation, wind speed, relative humidity, and solar radiation were supplied from 2,755 weather gridded-stations from the CFSR/NCEP dataset.

[12] HydroSHEDS reduces errors by deepening open water surfaces, weeding coastal zones, burning stream, filtering, moulding valley courses, filling sinks and carving through barriers.

We simulated monthly river flow for the whole watershed for the period January 1995 to July 2014. The simulation period was chosen to best fit the available performance data of hydropower plants, subject to the availability of weather data. The model was also run for 5 years prior to this period for warming up purposes, which helps to establish the equalized initial condition of soil water before simulation. The simulation used the method integrated in ArcSWAT (Arnold *et al.*, 1998; Neitsch *et al.*, 2009) that modify the SCS curve number procedure (SCS, 1972) to take into account the varying conditions of land uses and soil types to estimate surface runoff and use the Penman-Monteith method (Allen, 1986; Allen *et al.*, 1989; Monteith, 1981) to estimate evapotranspiration.

### 1.3.4 Hydropower Data Consolidation and Transformation

Our analysis focuses on river flow to the 40 largest hydropower plants in Vietnam, which belong to the 12 basins shown in Figure 1.2 and listed in Table 1.3. The location of these hydropower dams is mapped using a GIS software (ArcGIS) based on information from various sources including the Vietnam Energy Map of Japan External Trade Organization (JETRO), WB (2014), United Nations Framework Convention on Climate Change - Clean Development Mechanism (UNFCCC-CDM) database, hydropower companies' websites, and local news websites. Finally, we validated and refined the dataset using observations from Google Earth.

**[Figure 1.2 about here]**

**[Table 1.3 about here]**

Our hydropower operation data at the plant level is from Electricity of Vietnam (EVN, 2015). The report provides information on total capacity, monthly gauged river flow data of each plant, and electricity generation of 40 of the largest hydropower plants of Vietnam between 1995-2014. Vietnam classifies hydropower plants into two categories: small (under 30 MW and managed by local governments) and large (above 30MW and managed by central government).

WB (2014) further divides the latter group into medium (from 30MW to under 100MW) and large hydropower plants (above 100 MW). The majority of plants on our list of 40 are defined as large and all of them are managed by the central government. Figure 1.3 shows that the combined installed capacity of these plants accounts for 75-85% of all hydropower sources which in turn accounts for 35% -53% of all energy sources across Vietnam.

**[Figure 1.3 about here]**

As part of the data cleaning process we transformed the data in a number of ways. The original power generation data was monthly and measured in million kWh. However, the number of days within a month varies between 28 to 31. Our solution is to divide the monthly electricity generation by the number of days per month and re-scale it into MWh. Initially we had a simple measure of the installed capacity of plants after full installation. However, as there were no additional developments to existing hydropower plants during our period of analysis, this variable is time-invariant and would be absorbed by the fixed effects in our regressions. In other words, under such circumstances, we would n2ed to exclude the capacity variable as there would be perfect multicollinearity between it and the dam fixed effects, which already capture any time-invariant dam-specific characteristics. To mitigate this, we take advantage of the fact that each plant is comprised of several generators that are typically commissioned at different times. More precisely, it can take a plant months or even years to be fully operational after the commissioning of its first generator. Hence, in reality the installed capacity of each plant is time varying during the installation phase and time-invariant from that point onwards. We gather information on the operation date of each generator from the website of plants or local online newspapers, and then adjust the installed capacity of each plant to reflect the real operation of each generator. Fortunately, the first run of each generator in a large hydropower plant is an important event to investors and local residents and hence this information is fully recorded. As a result, the installed capacity variable, after transformation, became time-varying and can be included in a regression with fixed effects. All plants in our sample are of the storage type and many have large government regulated reservoirs. The total capacity of reservoirs ranges from 30.4 million $m^3$ to 9.8 billion $m^3$ and the mean size is 1.1 billion $m^3$. [13]

To enable us to investigate the interaction between dams on the same river system, we need to determine the upstream-downstream relationship between dams. To do this we use the HydroSHEDS identifiers from the HydroBASINS dataset at the most disaggregated level. HydroBASINS provides two systems of basin coding: HydroSHEDS identifiers and Pfafstetter code (Verdin and Verdin, 1999). We use the former as the HydroSHEDS identifiers is more consistent and each sub-basin is assigned one unique identifier and routed to (only) one immediate downstream sub-basin or the sea/itself (if it is an outlet) or an outlet (if it is an endorheic sink).[14] Table 1.4 shows that, after tracing all routes, that there are 13 hydropower cascades detected in 9 of the 12 basins studied comprised of 36 upstream-downstream pairs. We then consolidated with local information (websites of hydropower plants, local newspapers and so on). The distance between each upstream plant and its downstream counterparts in Table 1.4 is measured by the number of HydroSHEDS sub-basins shared between them. The exception is Ham Thuan and Da Mi where the zero-distance reflects the fact that the dams are located in the same sub-basin.

**[Table 1.4 about here]**

We create two proxies for the operation of an upstream dam: the combined installed capacity of upstream dams and the combined production of upstream dams. Some dams have many upper dams that are operated at different times and we need to fill in all missing values before aggregating. The installed capacity and production of plants before they begin their operation are assigned zero values. Any missing values from upstream dams are filled in using the predicted values of a double log regression of non-missing production values on its installed

[13] Information about these reservoirs is from the 11 most recent PM decisions on inter-reservoir management procedures in 11 basins: Ba (1077/QD-TTg -2014), Sesan (1182/QD-TTg 2014), Srepok (1201/QD-TTg 2014), Ca (2125/QD-TTg 2015), Huong (2482/QD-TTg 2015), Kon Ha Thanh (1841/QD-TTg 2015), Ma (1911/QD-TTg 2015), Tra Khuc (1840/QD-TTg - 2015), Red River (1622/QD-TTg -2015), Vu Gia Thu Bon (1537/QD-TTg 2015), Dong Nai (471/QD-TTg -2016). For smaller reservoirs, data were collected from internet sources. The smallest plant among those studied has a full installed capacity of 44 MW. The largest one is more than 50 times greater (2,400 MW) and the average one is about 300 MW.

[14] Because of the challenges in the latter in determining the downstream plants; for example, the difference in routing between inter-basins and basins and the skip of coding due to endorheic sinks and islands.

capacity and simulated discharge.[15] The double-log regression has lower predictability than the double-level regression; however, it ensures that the predicted values are positive. The variable coefficients then measure the average impact of upstream dams nationwide.

Table 1.5 provides summary statistics for our key variables of interest. We model monthly hydropower generation using data on installed capacity and simulated discharge. We consider the period from January 1995 to July 2014 and since the majority of Vietnam's hydropower plants were commissioned after 1995, the panel is unbalanced. Our final sample includes 2,984 observations with a mean generation of 4.39 MWh per day. The highest production record is 46.8 MWh (Son La on August 2014). Recall that the installed capacity, disaggregated at the generator level, is time variant and ranges from 22MW to 2,400 MW with a mean of 376.3 MW. The simulated flows in the sample vary from 0.12 – 9,105 cubic metres per second and the combined installed capacity of upstream dams varies from 0 to 2,820 MW. The combined production of upstream dams varies from 0 to 45,781 MWh/day.

**[Table 1.5 about here]**

### 1.3.5 Simulation Validation

To evaluate the performance of the river flow model in general and the SWAT application in particular, a common approach is to compare the gauged flow with the simulated flow based on statistics established and documented prior to the modelling. There are numerous statistics that can be used for this purpose that are usually put into 3 different categories: standard regression, dimensionless, and error index (Moriasi *et al.*, 2007). In this study, since river flows are simulated to serve as as an explanatory variable in subsequent regression analyses, we are interested in the variation in discharge rather than the level. Hence, for validation we intend to use two standard regression statistics: Pearson's correlation coefficient $r$ and the coefficient of determination $R^2$. The gauged data for validation are monthly average inflows to dams from the

[15] The model for each plant ($i$) is $ln(Gen_t) = \beta_0 + \beta_1 ln(CAP_t) + \beta_2 ln(Flow_t) + \varepsilon_t$.

same source as hydopower generation data. The data are only available for dams during their operation time hence the length of gauged series vary across dams. It should also be noted that there are many missing values hence gauged series are shorter than the generation series. Validation is applied for dams with gauged series long enough (at least 30 observations) to provide statistically reliable results.

Pearson's correlation coefficient $r$ measures the degree of the linear relationship between two types of data, ranging from -1 (perfect negative correlation) to 1 (perfect positive correlation) (Krause *et al.*, 2005; Moriasi *et al.*, 2007). To have confidence in our simulated data we expect a sensible river flow model to have a positive $r$ with a magnitude close to one. As we do not have any guide on specific threshold to classify the fit of the model based on $r$, we report the significance at conventional levels (i.e., whether two variables are significantly correlated or not).

$$r = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)\left(Y_i^{sim} - \bar{Y}^{sim}\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i^{sim} - \bar{Y}^{sim}\right)^2}} \tag{1.2}$$

The coefficient of determination R-squared measures the percentage of the change in observed data explained by a best-fit regression line using simulated data as an explanatory variable. The value is bounded between 0 and 1, and the higher it is, the better the match between observed data and simulated data. A value above 0.5 is considered acceptable (Santhi *et al.*, 2001; Van Liew *et al.*, 2007).

### 1.3.6 Regression Method

To estimate hydropower generation using simulated flows, we rely on the linear panel data model and the pooled ordinary least squares (POLS) estimator. See Appendix 1.A for more details. For inference purposes, we make minimal assumptions about the error term and rely on standard errors that are robust to heteroscedasticity and contemporaneous and lagged spatial correlation computed by statistical package STATA and command *xtscc* (Hoechle, 2007). They are derived from the non-parametric covariance matrix estimator by Driscoll and Kraay (1998) adjusted for an unbalanced panel . Driscoll and Kraay (1998) standard errors are used because the normal i.i.d assumptions are not appropriate as the variances in the errors are likely to be larger for the larger plants. In addition, power generation from different plants, especially those within the same basin, are likely to be correlated with each other. Finally, the electricity generation from any given plant at a particular time is not independent of its lagged values. To assess the goodness-of-fit of our models, we consider the adjusted R-squared ($\bar{R}^2$) that measures the percentage of variation in the dependent variable explained by a model with a penalty for excessive regressors. We employ a number of specifications to model hydropower generation as follows:

**Baseline regression** In the first stage we examine the degree to which simulated river flow explains the production of electricity from hydropower plants. Our baseline specification follows Cole *et al.* (2014) and assumes that the main determinants of hydropower generation (*Gen*) are a quadratic function of river flow (*Flow)* and dam capacity (*CAP*):

$$Gen_{it} = \beta_0 + \beta_1 Flow_{it} + \beta_2 Flow_{it}^2 + \beta_3 CAP_{it} + \lambda_t + \mu_i + \varepsilon_{it} \tag{1.3}$$

where subscripts $i$ and $t$ refer to a hydropower plant and our unit of time, respectively. $\lambda_t$ is included to capture all time-specific factors (monthly) that have a uniform effect on all hydropower plants. $\mu_i$ is the unobservable time-invariant hydropower plant fixed effect and $\varepsilon_{it}$ is an idiosyncratic error term. One should note that our specification differs from Cole *et al.* (2014) in that they studied hydropower generation on a continental scale for Africa at yearly intervals, while our study is on a national scale for Vietnam using monthly data.

The calculation of electricity production from a hydropower plant is given by:

$$P = \eta \times \rho \times g \times Q \times H \tag{1.4}$$

where $P$ is the power produced at the transformer (million MW), $\eta$ is the overall efficiency of the power plant, $\rho$ is the density of water (1000 kg/m$^3$), $g$ is the acceleration due to gravity (9.81 m/s2), $Q$ is the volume flow rate passing through the turbine (m$^3$/s), and $H$ is the net head (m). By assigning a typical overall efficiency of 87% (IFC, 2015) it reduces the formula to:

$$P(kW) = 8.5 \times Q \times H \tag{1.5}$$

The installed capacity is one of the most prominent features of a hydro plant, which can be calculated by equation (4) using design discharge, net head, and the overall efficiency for a given design discharge. If the river flow rate passing through a turbine is equal to its design discharge, the production of electricity is proportionate to the installed capacity. If the flow rate is higher or lower than the design discharge, there will be more or less electricity generated. The gap between the flow rate and the design discharge can be sensibly proxied by the variation in the river flow into a hydropower plant. We expect positive signs for both explanatory variables in a linear specification ($\beta_1, \beta_3 > 0$). The linear function of the inflow's impact on hydropower electricity generation is based on the assumption of constant overall efficiency. In practice, efficiency is a non-linear function of the deviation between the turbine discharge and the optimal value, the outcome of which is subject to the type of turbine. Figure 1.4 presents a stylized version of the efficiency profiles of different turbine types and shows that plant efficiency is low when the discharge is far below the optimal value, and then increases. This suggests that a quadratic function of discharge with a negative coefficient for the squared term ($\beta_2 < 0$) is a more appropriate functional form to model hydropower production.

**[Figure 1.4 about here]**

Besides the key determinants, our baseline model includes two-way fixed effects ($\lambda_t$+$\mu_i$+$\varepsilon_{it}$).

Dam fixed effects $\mu_i$ are included to account for the unobserved features that are unchanged overtime. As our SWAT model has not been calibrated, the parameters in the rainfall-runoff model can not be considered optimal. Hence, the relationship between simulated and actual inflows into a dam depends in part on the heterogeneous characteristics of each sub-basin (for example soil composition, land cover distribution and topographic features) and are partially absorbed by dam fixed effects. Dam fixed effects also capture variations in turbine efficiency across dams. We include time fixed effects to control for common trends over time. For example, the performance of satellite data on which our SWAT model relied may varying across the months of a year and across years. Likewise, time fixed effects will control for any time-varying fluctuations in the demand for electricity that is common across the country. Finally, besides measurement error, the idiosyncratic error term ($\varepsilon_{it}$) captures any unobserved factors that vary across either time or dams, for example, production adjustments due to regional changes in demand, deviations from overall turbine efficiency, the storage and releasing of water from dam reservoirs, and any hydropower plant interactions.

**Flood control regression** A key feature of hydropower plants is they important role they play in flood control. In Vietnam, 3 basins have reservoirs with a flood control capability namely Hong–Thai Binh River, Ma River and Huong River (MONRE, 2012).[16] Even hydropower plants without a specific flood control function are able to store flood water as a means to smooth electricity production across time.

To quantify the degree to which the flood control function of dams affects production of hydropower we extend the baseline specification to include proxies for floods. We estimate three alternative specifications: (1) a dummy variable $Flood_{it}$ (defined as flows that exceed the mean flow at each hydropower plant by at least one standard error), and (2) the flood dummy and its interaction terms with inflows into hydropower plants. The final specification is given

[16]Lo–Gam–Chay River and Da River are parts of larger Hong–Thai Binh River.

by:

$$Gen_{it} = \beta_0 + \beta_1 Flow_{it} + \beta_2 Flow_{it}^2 + \beta_3 CAP_{it} + \gamma_0 Flood_{it} + \gamma_1 Flow_{it} \times Flood_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (1.6)$$

where the assumption is that utilizing a dam's flood control role is at the expense of a reduction in hydropower generation even though this shortfall in power generation may be considered socially and economically desirable. We expect the estimated coefficients on our flood variables to be negative ($\gamma_0, \gamma_1 < 0$).

**Dam interactions** Finally, a little understood issue is how hydropower plants interact with each other. Hydropower generation in many basins requires coordination between plants that share a common water resource. Knowledge of how these interactions work could facilitate improvements in the allocation of existing water resources.

There are a number of reasons why an upstream plant may potentially influence the power generation of downstream plants that can be related to either their construction or operation. For example, the building of a hydropower plant is typically associated with a degree of deforestation and hence an increase in river-runoff. As a result, downstream discharge and electricity generation may increase.[17] Alternatively, some hydropower plants construct weirs that diverts water to an 'off-site' facility that enables it to create a higher head for electricity generation (Hecht and Lacombe, 2014) but at the cost of a reduction in river flow into downstream rivers which in turn lowers the production of hydropower plants in those down stream locations. In terms of operation, upstream plants with large storage facilities and no water diversion normally adjust outflows in a way that favours downstream electricity generation. By reducing extreme inflows into downstream plants it means that the turbines can operate at higher efficiency levels leading to higher levels of electricity production.

[17] A report from the National Assembly reveals that 160 hydropower projects in 29 cities and provinces over the period 2006-2012 converted an area of 19,792ha of forest land into land suitable for the location of hydropower plants (Le and Tran, 2016).

The actual effect of dam interactions is therefore an empirical question. To capture the cascade effect our solution is to include a proxy for the operation of upstream dams into our baseline specification. As part of our robustness checks we include the combined upstream capacity and combined upstream production variables (as described in Subsection 1.3.4). We further decompose the impact of cascades by adding interaction terms between upstream operation variables and categorical variables of hydrological conditions (flood, normal and drought). Finally, we investigate the heterogeneity in dam interaction across basins. According to PanNature (2011), basin-based water management was adopted in Vietnam fairly early.[18] As basins have historically been managed by different organizations, dam interaction could vary across basin. We explore this heterogeneity by adding the interaction terms between the proxies for upstream operation and dummies for each basin.

## 1.4 Results and Discussions

### 1.4.1 Simulated Discharge Validation

The validation is made for simulated inflows to 24/40 studied hydropower dams (belonging to 11/12 studied basins) that have at least 30 gauged observations for comparison.[19] The assessment results are shown in Table 1.6. Overall, all simulated flows are positively correlated with the gauged flows. The magnitude of the Pearson correlation coefficients ($r$) ranges from 0.33 (An Khe - Kanak) to 0.90 (Thac Mo). The mean and median of these coefficients are 0.70 and

[18]Water Resources Law issued in 1998 sketched river basin plan regulation and the role of the River Basin Planning Management Commissions. The commissions then established the management of water resources in Cuu Long (Mekong) River (2001), Dong Nai River (2001), Hong–Thai Binh River (2001), Vu Gia–Thu Bon (2005) by MARD. Similarly, River Basin Councils with the participation of local governments and the involvement of communities were created to manage the Srepok River (2006) and Ca River. Subsequently, the water resource management function was passed from MARD to the newly set-up MONRE with the establishment of a number of River Basin Environment Protection Commissions in Cau River (2007), Dong Nai River (2008), and Nhue-Day River (2009). The ineffectiveness of various basin management organizations mentioned above was addressed by the Decree 120/2008/ND-CP on River Basin management, which sought to establish consistent basin-based water resources management and proposed the establishment of the River Basin Commissions to coordinate and supervise the activities of ministries, and local governments related to water resources planning and management.

[19]The only basin that has no dam validated is the Huong River Basin.

0.72 respectively. Almost every correlation is significant at 1%. The exceptions are An Khe - Kanak and Quang Tri, which are significant at 10% and 5% respectively. The coefficients of determination ($R^2$) vary between 0.11 and 0.8. Based on the threshold of 0.5 for the this statistic, our rainfall-runoff model could be labelled as 'acceptable' for inflows to 13/24 dams. Both the mean and median of these $R^2$ are 0.52 and exceed the threshold.

**[Table 1.6 about here]**

There are a number of reasons why the simulated data does not perfectly match the observed data. Firstly, the model may inherit errors in the data, especially when we need to rely on remote-sensing data for our large scale study. For example, the HydroSHEDS dataset is known to be exposed to error in coastal areas (Lehner, 2013) due to SRTM satellite operation characteristics (Farr *et al.*, 2007). The problem is amplified as Vietnam is a coastal country and stretches along the sea. Our model perform better for basins in the North and the South rather than those in the Central part of the country. It is indeed difficult to accurately model discharge in small, narrow coastal basins like Huong River, or Thach Han River due to the strong influence of the tide. In addition, we simulated the model with assumptions of no change in topography, soil profile and land cover. We acknowledge that this is a reasonably strong assumption over a long period of time.

As our time period covers a time when Vietnam experienced rapid economic development, the change in land cover could be considerable (for example deforestation and urbanization). A boom of hydropower in Vietnam and countries upstream may also have a considerable impact on river flow regimes and sediment patterns. Finally, as our SWAT model was not calibrated, the default parameters that we rely on may not be optimal for Vietnam. An appropriate adjustment of the parameters ET, lateral flow, surface runoff, return flow and tile flow processes (Arnold, Moriasi, *et al.*, 2012) may improve the performance of the model. However, we were not able to execute such an approach in this study due to a shortage of longer observed flows that would be necessary for calibration.

Nevertheless, by exploiting information on the variation of discharge data rather than its level, the simulated flows appears to be useful given the significant and relatively high correlation with gauged flows. The introduction of fixed effects and dam interconnection modelling in regressions are expected to help mitigate some of the problems mentioned above. The above assessment also indicates that there are substantial similarities in SWAT model performance for dams in the same basin. This is a signal of potential spatial correlation besides possible serial correlation and motivates our decision to adjust the standard errors following Driscoll and Kraay (1998). See subsection 1.3.6 for details.

### 1.4.2 Regression Results

#### 1.4.2.1 Hydropower Generation (Baseline Model)

First, to arrive at the baseline specification we add each regressor sequentially which enables us to consider the contribution of each explanatory variable to the operation of hydro-plants. The results from Columns (1) to (5) in Table 1.7 show that all the regressors in the baseline specification appear with the expected signs and significance at the conventional levels. Column (1) shows that discharge is the main explanatory variable for hydropower electricity production with its variation alone explaining 64.4% of the variation in electricity generation. The non-linear specification in Column (2) provides additional explanatory power and adds 1.5% to the goodness-of-fit. A negative and significant quadratic term suggests that higher discharge increases production but at a decreasing rate before it reaches a turning point. Our finding is similar to that for African hydropower production shown in (Cole *et al.*, 2014). The reason for the inverted U is due to the variation in efficiency of turbines discussed in Subsection 1.3.6.[20] In Column (3) we include installed capacity which is found to be positive and significant and increases the adjusted R-squared by a further 19.3-percentage points to 0.853 and reduces the coefficients on both discharge and its squared term by roughly a half. The inclusion in Columns

[20]The average turning point is estimated to be approximately 9,820 ($m^3/s$), which is out of range of the discharge sample.

(4) and (5) of plant and time fixed effects respectively only marginally increases the goodness of fit. Our final baseline specification in Column (5) explains 87.7% of the variation in hydropower electricity generation.

**[Table 1.7 about here]**

#### 1.4.2.2 Flood Control

Column (6) of Table 1.7 includes a dummy for a flood and indicates that, on average, a plant during those months of flooding produces 795.5 MWh per day less than during normal operation conditions (which is equivalent to 18.2% of the mean production of the sample). When we add both a dummy for a flood and its interaction term with discharge in Column (7), only the coefficient of the latter is statistically different from zero and the estimate of the coefficient is just below -1 ($m^3/s$). It should be noted that as we do not model dynamics, the sacrifice of electricity generation for flood control purposes should be interpreted as a contemporaneous response rather than a permanent trade-off.[21] Dams can use water stored during periods of flooding to generate electricity at a later date. The large and significant coefficients estimated here provide evidence of the substantial benefits of large dams to mitigate the adverse impact of extreme weather events.

#### 1.4.2.3 Hydropower Plant Cascade Interactions

In Table 1.8 we present our estimates for the impact of hydropower cascades on hydropower production. In addition to our proxy for the operation of upstream dams we also include year and dam fixed effects. Our upstream dam proxies in Columns (1) and (3) are the sum of hydropower capacity installed upstream and the sum of hydropower generated upstream. The results show that upstream plant have a positive and significant impact on hydropower production although capacity is only significant at the 10 percent level. The interpretation of the

[21] We thank an anonymous referee for raising this point.

coefficients is straightforward. Each additional MW of hydropower capacity installed upstream increases the daily production of a downstream plant by 1.332 MWh (Column 1). This is equivalent to 0.03% the mean production of the sample. Column (3) shows that an increase by 1 MWh in the production of upstream plants adds 0.146 MWh to downstream production.

**[Table 1.8 about here]**

In Columns (2) and (4) we include interaction terms to evaluate the synergies under different hydrological conditions. Column (2) suggests that for downstream electricity generation, on average each extra MW upstream adds 1.28 MWh in normal conditions, 2.721 MWh under extremely dry conditions and reduces production by 0.167 MWh under extremely wet conditions. Column (4) indicates that a 1 MWh increase in upstream production induces a rise in downstream production by 0.161 MWh under normal discharge conditions, by 0.0634 MWh under flood conditions and 0.341 MWh in a drought. The differences between the coefficients under extremely dry conditions and normal conditions is significant at the 1% level.

Our results highlight that hydropower cascades can be successfully used to improve the reliability of power supply and as an adaptation measure against future extreme weather conditions. During period of drought an upstream plant can roughly double the production of downstream plants but has a negligible effect during extreme wet conditions. The logic is simple. Upstream plants store water during floods and release water during droughts, which in both cases improves the efficiency of downstream plants.

To investigate the cascade effect further, in Table 1.9 we include hydropower dam interactions at the basin scale. Since there are no cascades among the plants in the basins of the Thach Han River, Kon-Ha Thanh River and Vu Gia–Thu Bon River, the results in Table 1.9 estimate the spillover effects for 9 basins only.[22] Our results now suggest that the spillover effect of upstream plants is not always positive. While synergies are found for the Da River, Sesan River, and Srepok River, we find a negative spillover effect for the Dong Nai River, Ba River,

[22]The estimates for Ca River, Huong River and Srepok River using interaction terms for upstream dams installed capacity were dropped due to the perfect multicollinearity with dam fixed effects.

Ca River, Huong River, and Ma River. Although all of the positive synergies are significant, the only negative and significant impact is for the Dong Nai River and the Ca River.

**[Table 1.9 about here]**

An important question is whether these synergies were anticipated before the construction of new upstream plants. If this is the case, if well coordinated, the construction of an upstream plant can be equivalent to extending downstream storage such that downstream plants can store and release stored water to maximize power generation. An example of coordinated construction comes from Srepok where the construction of the Buon Tua Srah dam (86 MW) was predicted to enhance the generation of the Buon Kuop and Srepok 3 dams by 77 million kWh and 34.8 million kWh, respectively (VINACONEX, 2017). In the Da River basin, the installation of Son La dam (2400 MW), the largest hydropower dam of Vietnam (and in Southeast Asia), was expected to increase the annual production of Hoa Binh dam by 1.26 billion kWh (Vietnam National Committe on Large Dams and Water Resources Development, 2006). Similarly, the operation of Ban Chat dam (220MW), upstream of Son La dam since 2013, was expected to add nearly 0.4 billion kWh per year to two downstream dams (Vietnam National Committe on Large Dams and Water Resources Development, 2015). Finally, in the Sesan river, the most upstream hydropower plant (Plei Krong 1 – 100 MW) was supposed to increase the installed capacity of downstream plants (Yaly, Sesan 3 and Seasan 4) by 157.3 MW and to increase production by 217.1 million kWh/year (Ialy Hydropower Company, 2017)

The negative spillovers are most likely the result of the deliberate diversion of water by upstream dams. Given the multi-purpose nature of dams, this negative impact may be intentional. The claim is that the Dai Ninh dam and Dong Nai 3 dam in the Dong Nai River were constructed to help prevent flooding in downstream districts of Lam Dong province and to reduce the flooding pressure on the most downstream hydropower dams in this basin (Tri An dam) (Pham, 2014). At other times, droughts caused by hydropower dams is unintended and undesirable. One of the most frequently criticised is the case of An Khe–Kanak dam (173 MW) which, after starting operation, began to store water from the Ba River but to discharges water into the Kon River to create a higher head and to improve its own production (MONRE, 2012). The result was that a downstream segment of Ba River became dry and adversely affected the welfare of nearby residents.

Although our results are robust to different specifications, it is worth noting that while we control for dam heterogeneity and time heterogeneity, there may still be some omitted variable bias if there are unobserved factors that vary both spatially and temporally. One example might be variations in weather conditions such as temperature and rainfall which are correlated with discharge and therefore could simultaneously affect hydropower supply through changes in demand for electricity. In this case, hot weather induces higher demand for cooling. However, over our time period, power transmission and distribution in Vietnam was centrally managed which should mean that these factors have a uniform impact on plants and hence be absorbed by time fixed effects. In addition, as hydropower was the cheapest form of electricity generation, it is used to cover the base load and hence should be less sensitive to demand fluctuations than other energy sources. A second concern is that physical processes like land cover changes, soil degradation and sediment transportation that were excluded from our SWAT model, could bring about a degree of measurement error. For simplicity, we assume that this source of error is exogenous. Finally, Vietnam is located downstream of a large number of international rivers, such that upstream changes could affect the discharge into Vietnam's basins. Although our SWAT model already accounts for variations in weather in upstream sub-basins outside Vietnam, the construction and operation of neighbouring countries' hydropower plants is beyond the scope of this study. For example, the construction of new hydropower plants in China has been blamed for worsening the drought that hit Southeast Asia (The Diplomat, 2016). Vietnam and Laos are also predicted to be the most badly affected from the proliferation of new hydropower plants along the Mekong River (The Economist, 2012, 2016).

## 1.5 Conclusions

In this paper we apply the SWAT river flow model combined with regression analysis to explain the operation of hydropower plants on a national scale in a hydro-dependent country with a diversity of terrain and climate conditions. Although Vietnam has experienced a period of rapidly-growing demand for energy (12-15% per year), it also faces the challenge of potentially adverse impacts of climate change.

As far as we are aware, this is the first study to build a river flow model using SWAT for Vietnam as a whole. To take into account the high level of inter-connectivity between Vietnam's rivers and upstream sources beyond its border, the extent of our river flow model covers a large part outside Vietnam. It includes three inter-boundary basins: Red River, Vietnam Coast, and Lower Mekong River, in which Vietnam shares water resources with China, Laos, Cambodia, Myanmar and Thailand. The watershed of 977,964 $km^2$ is divided into 7,887 sub-basins with a mean area of 131.6$km^2$ and 53,024 HRUs. Such a detailed analysis is possible thanks to a variety of high-resolution datasets, especially HydroSHEDS/HydroBASINS, which is finer than Hyro1K and a topographic and hydrographic dataset widely used in previous economic studies using river flow models. River-flow was simulated for the period from 1995 to mid-2014, coinciding with a period when both power supply and power demand of Vietnam increased dramatically. Since it is mainly dependent on global datasets derived from satellite data, the method described within this study could be easily replicated for other countries and regions.

Our regression analysis uses panel data fixed effects regression models to explain the operation of large hydropower plants across Vietnam. Simulated discharge is shown to be a good proxy for inflows into hydropower plants. Our results are similar to those of Cole *et al.* (2014) and show that installed capacity and a quadratic function of discharge are the key determinants of hydropower generation. Furthermore, our model shows evidence of a flood control benefit of large hydropower plants across Vietnam.

To summarise, our research addresses a number of concerns mentioned in the introduction.

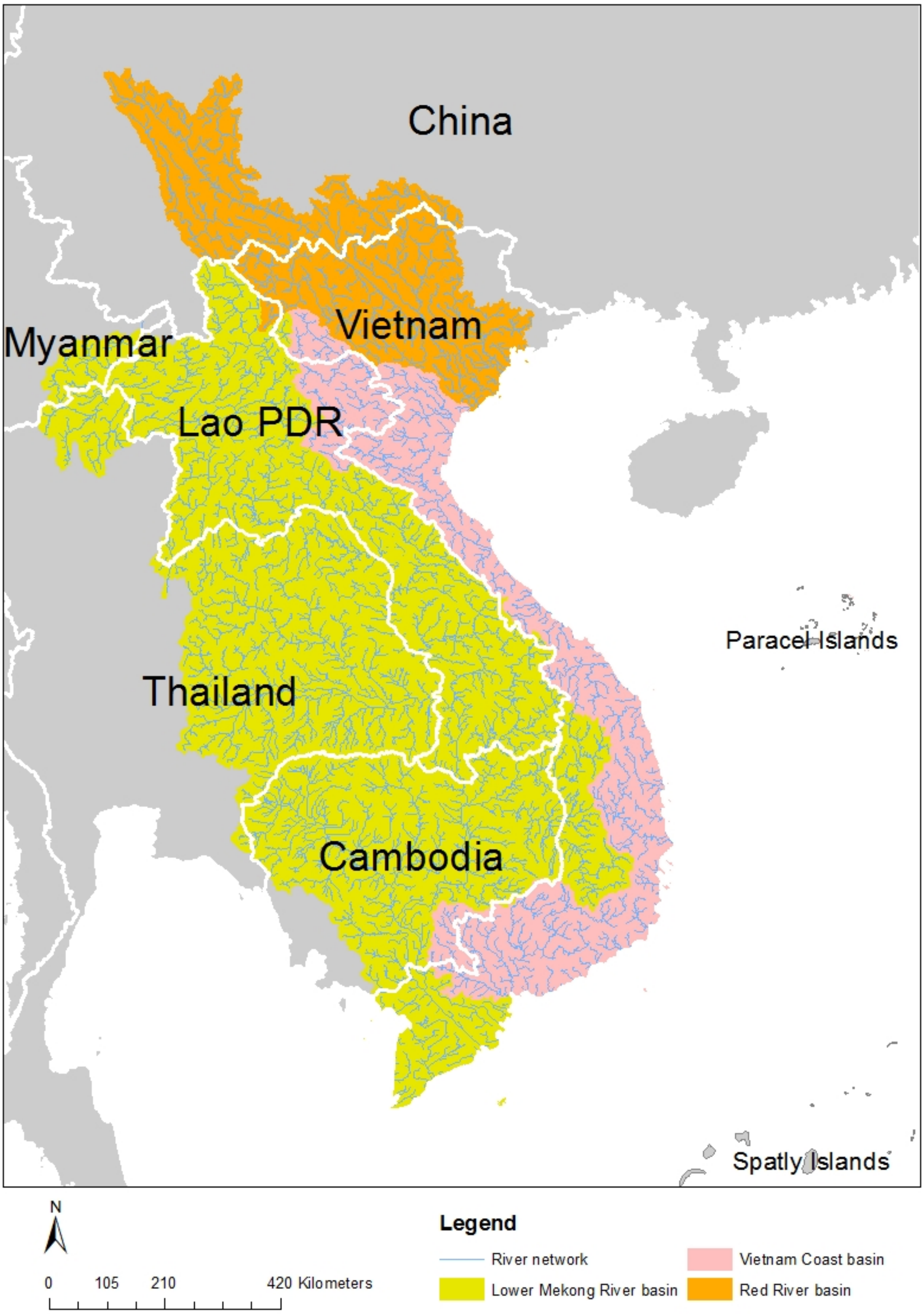
First, the national hydropower generations are shown to be sensitive to weather variations and badly affected by extreme hydrological regimes. Second, the multiple purposes of hydropower imply a trade-off relationship such that large dams actively cut down on average around 18.2% of their contemporaneous production in order to lower the damages of floods to downstream regions. Third, the current location of large hydro dams across Vietnam seems to be reasonable to create synergies between dams though in several basins the cascade effect is found to be negative because of either intentional design of flood reduction or weaknesses in management and coordination between dams.

In future research it would be interesting to also consider more carefully changes in power demand, land cover, soil degradation, and sediment transportation. In addition, more detailed calibration could improve the accuracy of the river flow model. However, due to current data limitations we leave this for future research. Nevertheless, using simulated discharge still manages to explain up to 87.7% of the monthly variation in hydropower generation (using the two-way fixed effect regressor including installed capacity, discharge and its squared term). This suggests that river flow simulated from a SWAT model, even without calibration, serves as a good predictor for hydropower electricity generation. We acknowledge that our flood measure is relatively coarse and is not able to capture all aspects of floods in a monsoon context (to be able to differentiate the impacts of beneficial vs disaster floods) and our static model of flood control benefit is not appropriate to model the long run impact. Improvements in either flooding data or dynamic modelling techniques would be useful for future research. Another potential benefit of dynamic modelling techniques that have not been included in this study is to better explore the storage operation of reservoirs and examine how past flows affect the generation of hydropower dams. Finally, our study concentrates on large dams and excludes the impact of medium and small plants, which grew dramatically after 2010 and may impact the hydropower plant cascade effect. Compared to large hydropower plants, the lack of supervision, coordination and regulation with regards to the construction and operation of small and medium hydropower in Vietnam is problematic (PanNature, 2010). Hence, one should not generalize the results in this paper for hydropower dams of all sizes.

Our study has a number of policy implications. First, we provide evidence to that an hydropower operation with large reservoirs and cascades of hydropower plants can strengthen the resilience of the national power supply system against the adverse impact of future climate change. However, harmonizing the operation of plants that share common water resources is not simple, as evidenced by the finding of significant and negative spillovers for some basins. Finally, although we only quantify the impact of hydropower plants on downstream electricity generation, it is implicitly made clear that upstream plants can have an important impact on downstream flow regime (seasonality, water availability and so on). This implies potentially large impacts on downstream ecosystems and other economic activity using water resources (i.e. agriculture), as well as the welfare of downstream inhabitants. Given the numerous interconnections between Vietnam's rivers and those of its neighbours, our findings also raise concerns about possible hydro-ecological consequences associated with the proliferation of large upper dam projects on the Mekong River. The challenges associated with inter-basin dam operation management are likely to be even harder when cross-border coordination is required.

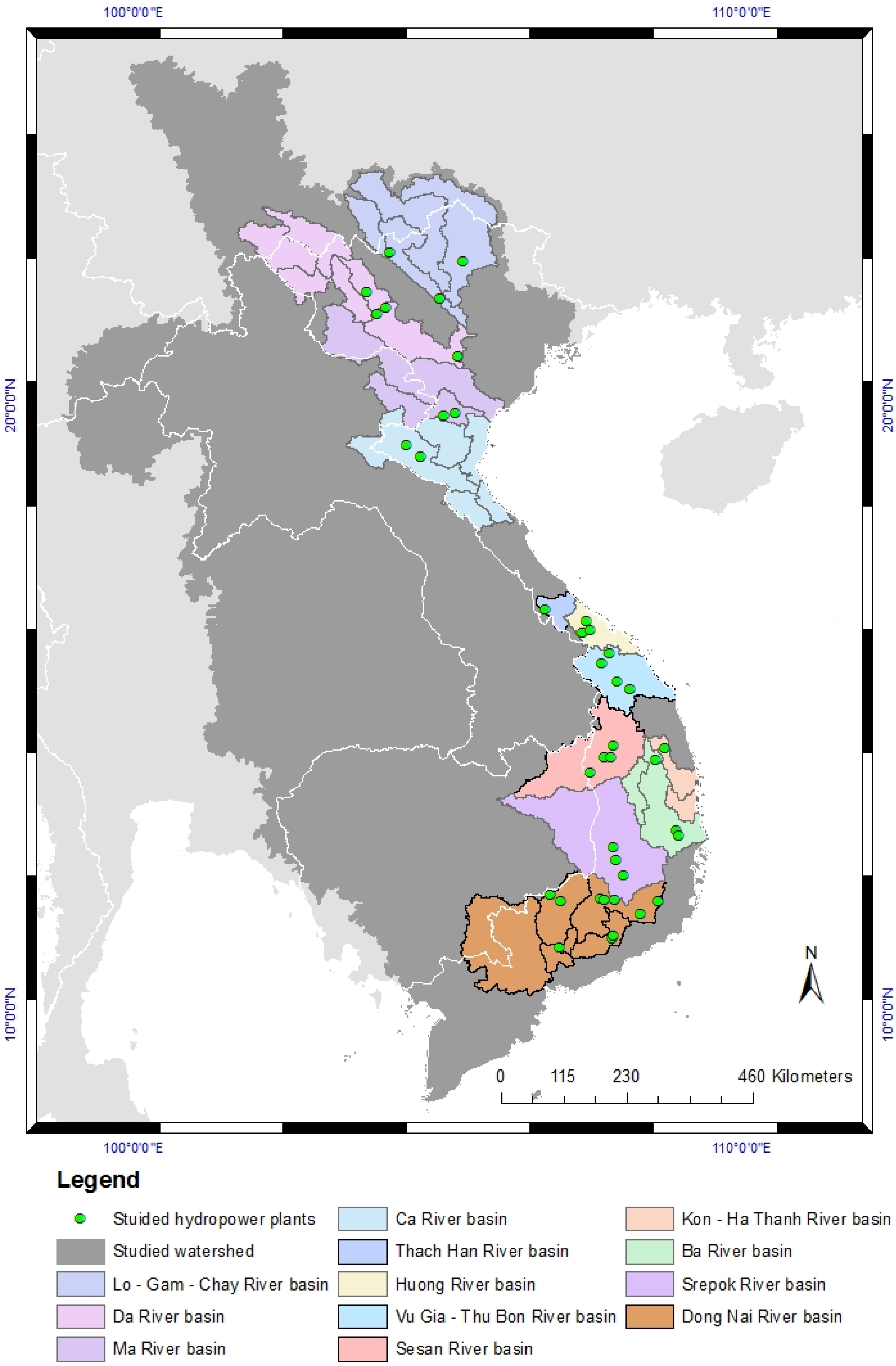
# Figures

**Figure 1.1: Watershed delineation**



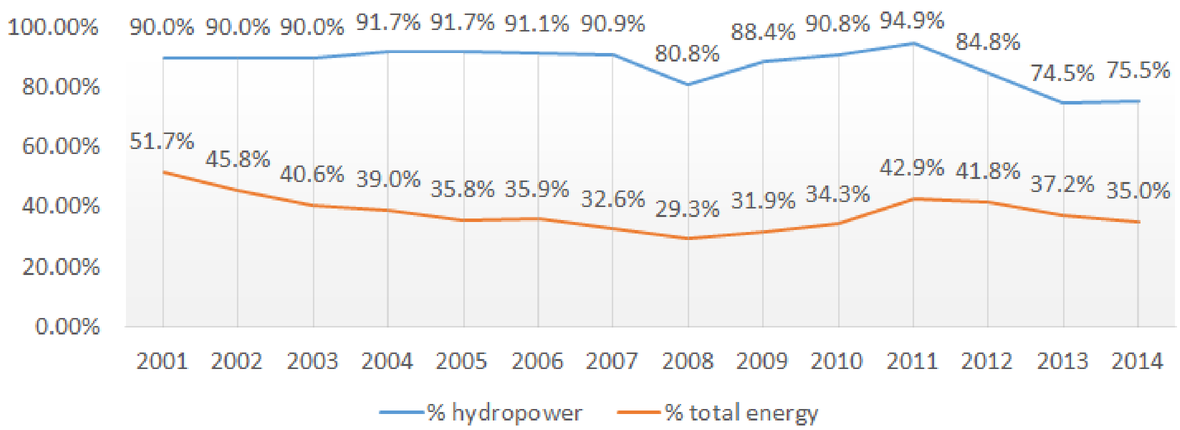

Source: Authors compiled from HydroSHEDS/HydroBASINS (Lehner *et al.*, 2008; Lehner and Grill, 2013) and 'Rivers in South and East Asia' (FAO, 2014). Note: The resolution of HydroSHEDS void-filled DEM is 3 arc-seconds. The resolution of HydroBASINS river network is 15 arc-seconds.

**Figure 1.2: Studied basins and hydropower plants**



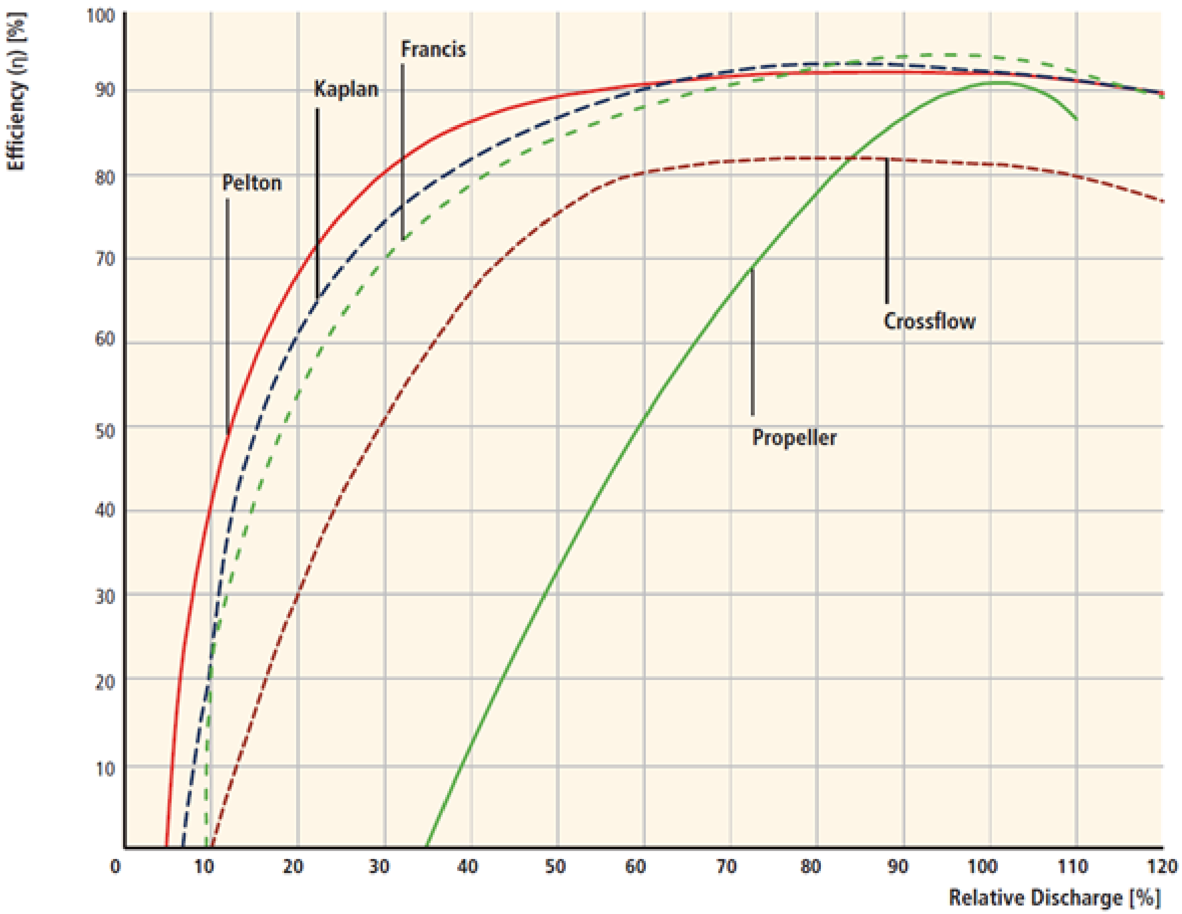

Source: Basins are derived from "FAO Rivers in South and East Asia" and MONRE (2012).

**Figure 1.3: Total installed capacity of studied hydropower plants, as percentage of national energy capacity**




Source: Authors calculated from EVN (2015).

**Figure 1.4: Typical efficiency curves for different types of hydropower turbines**




Source: (Kumar *et al.*, 2011, p. 453)

# Tables

**Table 1.1: Data description and sources for SWAT simulation**

| Data types | Sources | Resolution |
|---|---|---|
| Predefined basins | HydroBASINS<br>http://www.hydrosheds.org/page/hydrobasins | 15 arc-seconds |
| and river networks | Rivers in South and East Asia<br>http://ref.data.fao.org/map?entryId=dc2a5121-0b32-482b-bd9b-64f7a414fa0d | 30 arc-seconds |
| Digital Elevation Model (DEM) | HydroSHEDS void-filled DEM<br>http://www.hydrosheds.org/ | 3 arc-seconds |
| Soil | Digital Soil Map of the World version 3.6<br>http://www.fao.org/geonetwork/srv/en/metadata.show?id=14116 | 5 arc minutes |
| Land cover | UMD Land Cover classification collection<br>http://glcf.umd.edu/data/landcover/ | 1km pixels |
| Weather | CFSR-NCEP<br>https://globalweather.tamu.edu/ | 19 arc-seconds |

*Note:* See text for more details

**Table 1.2: Summary statistics of subbasins**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| VARIABLES | N | mean | sd | min | max |
| **All sub-basins within the watershed** | | | | | |
| Area of the sub-basin | 7,887 | 131.6 | 56.52 | 0.2 | 368.6 |
| Total upstream area | 7,887 | 15,443 | 77,756 | 0.4 | 774,282 |
| Distance to the next downstream sink | 7,887 | 951.4 | 754.4 | 0 | 3,628 |
| Distance to the most downstream sink | 7,887 | 957 | 751.3 | 0 | 3,628 |
| **Sub-basins within Vietnam** | | | | | |
| Area of the sub-basin | 2,617 | 131.9 | 58.4 | 0.2 | 368.6 |
| Total upstream area | 2,617 | 7,812 | 59,053 | 0.4 | 774,282 |
| Distance to the next downstream sink | 2,617 | 341.4 | 417.2 | 0 | 2,506 |
| Distance to the most downstream sink | 2,617 | 343.6 | 416.4 | 0 | 2,506 |

*Source:* Authors compiled from HydroBASINS dataset (level 12).

*Note:* N=Number of observations. sd= standard deviation

**Table 1.3: Studied hydropower plants**

| Basin | Dams |
|---|---|
| Lo - Gam - Chay | Thac Ba (120 MW), Tuyen Quang (342 MW), Bac Ha (90 MW) |
| Da | Hoa Binh (1920 MW), Son La (2400 MW), Nam Chien (200 MW), Ban Chat (220 MW) |
| Ma | Hua Na (180 MW), Cua Dat (97 MW) |
| Ca | Khe Bo (100 MW), Ban Ve (320 MW) |
| Thach Han | Quang Tri (64 MW) |
| Huong | A Luoi (170 MW), Binh Dien (44 MW), Huong Dien (71 MW) |
| Vu Gia – Thu Bon | Song Tranh 2 (190 MW), Dak Mi 4 (190 MW), A Vuong (210 MW), Song Con (63 (MW) |
| Kon – Ha Thanh | Vinh Son (66 MW) |
| Sesan | Sesan 4 (360 MW), Sesan 3 (260 MW), Yaly (720 MW), Plei Krong 1 (100 MW) |
| Ba | Song Hinh (70 MW), Song Ba Ha (220 MW), An Khe-Knak (173 MW) |
| Srepok | Buon Tua Srah (86 MW), Buon Kuop (280 MW), Srepok 3 (220 MW) |
| Dong Nai | Tri An (400 MW), Da Mi (175 MW), Ham Thuan (300 MW), Dai Ninh (300 MW), Da Nhim (160 MW), Thac Mo (150 MW), Dong Nai 3 (180 MW), Dong Nai 4 (340 MW), Dak R'Tih (144 MW), Can Don (78 MW) |

## Table 1.4: The cascades of hydropower

| **Updam** | **Bac Ha** | **Ban Chat** | **Nam Chien** | **Hua Na** | **Ban Ve** | **A Luoi** | **Plei Krong 1** | **An Khe - Kanak** | **Buon Tua Srah** | **Thac Mo** | **Da Nhim** | **Dai Ninh** | **Ham Thuan** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Basin* | *Lo - Gam - Chay* | *Da* | *Da* | *Ma* | *Ca* | *Huong* | *Sesan* | *Ba* | *Srepok* | *Dong Nai* | *Dong Nai* | *Dong Nai* | *Dong Nai* |
| **Distance** | | | | | | | | | | | | | |
| 0 | | | | | | | | | | | | | Da Mi |
| 1 | | | | | | | | | | | | | |
| 2 | | | | Cua Dat | | Huong Dien | | | | Can Don | | | |
| 3 | | | | | Khe Bo | | Yaly | | | | | | |
| 4 | | Son La | | | | | Sesan 3 | | Buon Kuop | | | | |
| 5 | | | | | | | | | | | | | |
| 6 | | | | | | | | | | | | Dong Nai 3 | |
| 7 | | | | | | | | | | | | Dong Nai 4 | |
| 8 | | | | | | | Sesan 4 | | Srepok 3 | | Dong Nai 3 | Dak R'Tih | |
| 9 | | | | | | | | | | | Dong Nai 4 | | |
| 10 | | | | | | | | | | | Dak R'Tih | | |
| 14 | Thac Ba | | | | | | | | | | | | |
| 15 | | | | | | | | | | | | | Tri An |
| 16 | | | | | | | | | | | | | |
| 17 | | | | | | | | | | | | | |
| 18 | | | | | | | | Song Ba Ha | | | | | |
| 20 | | | Hoa Binh | | | | | | | | | | |
| 21 | | | | | | | | | | | | | |
| 23 | | | | | | | | | | | | Tri An | |
| 25 | | Hoa Binh | | | | | | | | | Tri An | | |

The upstream-downstream relationship was determined by the HydroSHEDS ID system of HydroBASINS dataset.
Distance was measured by the number of sub-basins (at level 12 of HydroSHEDS dataset) between each upstream and downstream dams.

Table 1.5: Summary statistics

| VARIABLES | (1) N | (2) mean | (3) sd | (4) min | (5) max |
|---|---|---|---|---|---|
| **Dam statistics** | | | | | |
| Year of Operation | 40 | 2005 | 10.5 | 1964 | 2013 |
| Total storage capacity (million $m^3$) | 40 | 1,164 | 2,098 | 30.4 | 9,862 |
| Full installed capacity (MW) | 40 | 294 | 455 | 44 | 2,400 |
| **Production statistics (Jan 1995 – Jul 2014)** | | | | | |
| Average production ($MWh/day$) | 2,984 | 4,393 | 6,754 | 0 | 46,833 |
| Installed capacity ($MW$) | 2,984 | 376.3 | 521.4 | 22 | 2,400 |
| Flow to dam ($m^3/s$); SWAT simulation | 2,984 | 465.5 | 979.5 | 0.120 | 9,105 |
| Upstream capacity ($MW$) | 2,984 | 141.9 | 360.9 | 0 | 2,820 |
| Upstream production ($MWh/day$) | 2,984 | 1,615 | 4,161 | 0 | 45,781 |

*Note:* N=Number of observations. sd= standard deviation

**Table 1.6: Simulated discharge validation**

| Dam | Basin | Capacity (MW) | N | $r$ | $R^2$ |
|---|---|---|---|---|---|
| Thac Ba | Lo - Gam - Chay | 120 | 235 | .82*** | .67* |
| Tuyen Quang | Lo - Gam - Chay | 342 | 70 | .8*** | .64* |
| Hoa Binh | Da | 1920 | 235 | .88*** | .78* |
| Son La | Da | 2400 | 43 | .81*** | .65* |
| Cua Dat | Ma | 97 | 31 | .75*** | .56* |
| Ban Ve | Ca | 320 | 31 | .68*** | .47 |
| Quang Tri | Thach Han | 64 | 31 | .41** | .17 |
| A Vuong | Vu Gia - Thu Bon | 210 | 31 | .6*** | .36 |
| Vinh Son | Kon - Ha Thanh | 66 | 209 | .7*** | .49 |
| Sesan 3 | Sesan | 260 | 31 | .54*** | .29 |
| Yaly | Sesan | 720 | 171 | .73*** | .53* |
| Plei Krong 1 | Sesan | 100 | 31 | .82*** | .68* |
| Song Hinh | Ba | 70 | 171 | .86*** | .73* |
| Song Ba Ha | Ba | 220 | 31 | .69*** | .48 |
| An Khe - Kanak | Ba | 173 | 31 | .33* | .11 |
| Buon Kuop | Srepok | 280 | 31 | .71*** | .5* |
| Tri An | Dong Nai | 400 | 235 | .82*** | .67* |
| Da Mi | Dong Nai | 175 | 122 | .42*** | .17 |
| Ham Thuan | Dong Nai | 300 | 160 | .53*** | .28 |
| Dai Ninh | Dong Nai | 300 | 70 | .68*** | .46 |
| Da Nhim | Dong Nai | 160 | 235 | .65*** | .42 |
| Thac Mo | Dong Nai | 150 | 223 | .9*** | .8* |
| Dong Nai 3 | Dong Nai | 180 | 31 | .85*** | .73* |
| Can Don | Dong Nai | 78 | 31 | .86*** | .74* |

*Note:* Capacity indicates full installed capacity. N indicates number of observations. Significance level for Pearson correlation coefficient ($r$): *** p<0.01, ** p<0.05, * p<0.1. For the coefficient of determination ($R^2$) to indicate acceptable model (Santhi *et al.*, 2001; Van Liew *et al.*, 2007): * ($R^2 \geq 0.5$).

**Table 1.7: Production regression using simulated discharge**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | Average production ($MWh/day$) | | | | | | |
| Intercept | 1,818*** | 1,382*** | 76.50 | 1,645*** | 901.4*** | 899.6*** | 826.9*** |
| | (155.3) | (121.4) | (106.5) | (217.7) | (229.7) | (232.8) | (236.1) |
| Flow to dam ($m^3/s$); SWAT simulation | 5.533*** | 7.459*** | 3.108*** | 4.198*** | 4.478*** | 4.627*** | 4.647*** |
| | (0.339) | (0.487) | (0.370) | (0.464) | (0.554) | (0.574) | (0.594) |
| Flow to dam ($m^3/s$); SWAT simulation squared | | -0.000392*** | -7.39e-05 | -0.000212** | -0.000228** | -0.000233** | -0.000105 |
| | | (0.000105) | (8.71e-05) | (8.64e-05) | (9.24e-05) | (9.25e-05) | (0.000118) |
| Installed capacity ($MW$) | | | 7.858*** | 6.319*** | 5.856*** | 5.904*** | 5.996*** |
| | | | (0.375) | (1.118) | (1.186) | (1.185) | (1.190) |
| Flood | | | | | | -795.5*** | -48.06 |
| | | | | | | (266.1) | (286.5) |
| Inflow*Flood | | | | | | | -0.981** |
| | | | | | | | (0.454) |
| Observation number | 2,984 | 2,984 | 2,984 | 2,984 | 2,984 | 2,984 | 2,984 |
| R-squared | 0.644 | 0.660 | 0.854 | 0.875 | 0.889 | 0.890 | 0.892 |
| Adjusted R-squared | .644 | .659 | .853 | .873 | .877 | .879 | .881 |
| Dam dummies | | | | Y | Y | Y | Y |
| Time dummies | | | | | Y | Y | Y |

Driscoll-Kraay standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

**Table 1.8: The synergies of hydropower cascades**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | Average production ($MWh/day$) | | | |
| *Variables for dam operation* | | | | |
| Installed capacity ($MW$) | 5.876*** | 5.880*** | 5.859*** | 5.834*** |
| | (1.182) | (1.176) | (1.190) | (1.184) |
| Flow to dam ($m^3/s$); SWAT simulation | 4.476*** | 4.984*** | 4.359*** | 4.865*** |
| | (0.544) | (0.554) | (0.559) | (0.568) |
| Flow to dam ($m^3/s$); SWAT simulation squared | -0.000225** | -0.000275*** | -0.000216** | -0.000267*** |
| | (9.19e-05) | (9.17e-05) | (9.14e-05) | (9.11e-05) |
| *Variables for upstream dam operation* | | | | |
| Upstream capacity ($MW$) | 1.332* | 1.280 | | |
| | (0.705) | (0.853) | | |
| Upstream capacity ($MW$)*Flood | | -1.447** | | |
| | | (0.689) | | |
| Upstream capacity ($MW$)*Drought | | 1.441** | | |
| | | (0.574) | | |
| Upstream production ($MWh$) | | | 0.146** | 0.161** |
| | | | (0.0598) | (0.0695) |
| Upstream production ($MWh$)*Flood | | | | -0.0976* |
| | | | | (0.0541) |
| Upstream production ($MWh$)*Drought | | | | 0.180*** |
| | | | | (0.0446) |
| Intercept | -429.8 | -553.0 | -430.3 | -523.5 |
| | (464.2) | (456.5) | (468.7) | (464.6) |
| Observation number | 2,984 | 2,984 | 2,984 | 2,984 |
| $R^2$ | .891 | .893 | .892 | .895 |
| Adjusted $R^2$ | .88 | .88 | .88 | .88 |

*** p<0.01, ** p<0.05, * p<0.1.
Dam fixed effects and time fixed effects are included. Driscoll-Kraay standard errors are in parentheses.

**Table 1.9: The synergies of hydropower cascades by basin**

| | (1) | | (2) | |
|---|---|---|---|---|
| VARIABLES | Average production ($MWh/day$) | | | |
| Installed capacity ($MW$) | 5.724*** | (1.165) | 5.716*** | (1.164) |
| Flow to dam ($m^3/s$); SWAT simulation | 4.719*** | (0.533) | 4.625*** | (0.545) |
| Flow to dam ($m^3/s$); SWAT simulation squared | -0.000247*** | (8.69e-05) | -0.000246*** | (8.54e-05) |
| Interaction: Updams operation*Ba | -3.818 | (2.699) | -0.170 | (0.247) |
| Interaction: Updams operation*Ca | | | -0.697* | (0.402) |
| Interaction: Updams operation*Da | 2.157*** | (0.783) | 0.220*** | (0.0685) |
| Interaction: Updams operation*Dong Nai | -2.136*** | (0.501) | -0.135*** | (0.0428) |
| Interaction: Updams operation*Huong | | | -0.618 | (0.711) |
| Interaction: Updams operation*Lo - Gam - Chay | 1.289 | (3.862) | -0.307 | (0.555) |
| Interaction: Updams operation*Ma | -1.495 | (2.252) | -0.166 | (0.222) |
| Interaction: Updams operation*Sesan | 2.314 | (9.777) | 0.215*** | (0.0427) |
| Interaction: Updams operation*Srepok | | | 0.577*** | (0.0639) |
| Observation number | 2,984 | | 2,984 | |
| $R^2$ | .896 | | .897 | |
| Adjusted $R^2$ | .885 | | .886 | |
| Upstream operation | Installed capacity | | Production | |

*** p<0.01, ** p<0.05, * p<0.1.
Dam fixed effects and time fixed effects are included. Driscoll-Kraay standard errors are in parentheses. Upstream operation indicates which variable is used to proxy for operation of upstream dams: (combined upstream) installed capacity (MW) or (combined upstream) production (MWh/day)

## 1.A Appendix A: Regression Estimators

Our method is based on the linear panel data model:

$$y_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it}; i = 1, 2, ..., N; t = 1, 2, ..., T$$

where $i$ and $t$ are respectively indices for dam and time, scalar $y$ is the dependent variable, $\mathbf{x}$ is a $K \times 1$ vector of independent variables, which may contain an intercept, dummies and non linear variable (interaction and/or quadratic terms). $\boldsymbol{\beta}$ is a $K \times 1$ vector of unknown coefficients, which are restricted to be common across time and dam. However, change in parameters across dam or time are permitted by the inclusion of appropriate regressors in $\mathbf{x}$ (for example time dummies or dam dummies).

Our coefficients are estimated using a pooled ordinary least squares (POLS) estimator:

$$\hat{\beta} = \Big(\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{x}'_{it}\mathbf{x}_{it}\Big)^{-1}\Big(\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{x}'_{it}y_{it}\Big) \tag{A1}$$

The estimator is shown to be consistent (Wooldridge, 2010, pg. 192) as long as $E(\mathbf{x}'_t\varepsilon_t) = 0$, for $t = 1, 2, ..., T$ (exogeneity condition) and $\text{rank}\Big[\sum_{t=1}^{T}E(\mathbf{x}'_t\mathbf{x}_t)\Big] = K$ (no perfect collinearity condition).

The goodness-of-fit of regressions are computed as:

$$R^2 = \frac{\sum(\hat{y}_{it} - \bar{y})^2}{\sum(y_{it} - \bar{y})^2} \tag{A2}$$

$$\bar{R}^2 = 1 - \frac{n-1}{n-K}(1 - R^2) \tag{A3}$$

where $\hat{y}_{it}$ and $\bar{y}$ are respectively the predicted values and the mean of the observed values of the dependent variable. $n$ is the number of observations. $R^2$ is bounded by 0 and 1. $\bar{R}^2$ never exceeds $R^2$ and can be negative if a poorly-performing model includes too many redundant regressors. In general, a model with higher $R^2$ or $\bar{R}^2$ fits the observed data better.

The two next appendices present some works excluded from the main text to reduce the lengthiness and improve the readability. They provide an in-depth analysis on some characteristics of the simulated flows (Appendix. 1.B) and a detailed comparison between the simulated flows and observed flows (Appendix 1.C).

## 1.B Appendix B: Seasonality, Trend and Stationary of Simulated Flows

In this section, we examine some important properties of the discharge series simulated from the SWAT model. Salas (1993) stated that a hydrological series can have various attributes and be decomposed into many components as trends, shifts (or jumps), seasonality, autocorrelation and non-normality. Without any particular trends, shifts, or periodicity, a hydrological process has a constant mean and variance, or other words, it is stationary. However, climatic variation on a large scale, natural disruptions, human activities and the annual cycle in minor step series typically induce non-stationarity into the hydrological process.

A thorough examination of discharge properties benefit this study in numerous ways. First, a strong seasonal pattern of discharge to hydro plants is the main driver of the cycle in hydropower production and causes power supply fluctuations. The electricity outage problem of Vietnam is mainly a result of the dry seasons when the discharge is low and the demand for electricity rises steadily due to hot weather and air conditioner use. Thus, examining the causes of this cycle is desirable. Second, the flows were simulated under the assumption that there was no change in the land cover. This implicitly excludes the impact of human activities including but not limited to deforestation, crop expansion and conversion, urbanization, dam construction and operation on hydrology. Hence, any trend (either deterministic or stochastic) detected in these series is, perhaps partially falsely, attributed with confidence to the change in climatic factors under the assumedly constant topographic and soil conditions. This allows us to investigate the link between global climate change and the local hydrological process without the concern over human influences and probably provides some future implications on the nature-induced variations in the chief input for hydropower. Finally, we may want to know whether the trends associated with the hydrographic series studied are deterministic or stochastic. In the former case, hydrological series tend to revert to the trend frequently as (weather) shocks gradually die out and forecast intervals have constant width. In the latter case, trend reversion is rare as (weather) shock have persistent effects and forecast intervals increase over time.

We start this section by fitting the simulated flows to a simple linear econometric model to detect the seasonality and deterministic trends. Then a seasonal non-parametric test is adopted to investigate the trend with the accompanying relaxed assumptions. Finally, we perform some unit root tests to learn about the stochastic trend (if any) associated with the series.

### 1.B.1 Seasonality and Time Trend

We analysed the seasonality of all simulated series of discharge to 40 large hydro-dams in Vietnam. As we did not have the full series for 2014 due to the unavailability of the weather data input, we only investigated the period from 1995 to 2013.

For each basin, we used a POLS model regressing the demeaned series on a full set of month dummy variables ($D_m$ ) and a time trend ($t$) and excluding constant term. This helps us avoid perfect collinearity and allows us to interpret the coefficients more easily. The regression can be explicitly expressed as follows:

$$Q_{it} - Q_i = \sum_{m=1}^{12} \beta_m D_m + \gamma t \tag{A4}$$

where $Q_{it}$ is the simulated flow to dam $i$ at time $t$ and $Q_i$ is the mean of simulated flows to dam $i$ across the studied period.

The coefficient of each month ($\beta_m$) indicates the gap between the average flow in that month and the average level of the whole year. Based on this, we roughly classified months with discharge above the annual mean (wet season with positive coefficients) and months with discharge below the annual mean (dry season with negative coefficients).

In Table 1.B.1, we present the results for the 12 basins that we study. The basins were sorted based on their location from the North to the South. The dashed lines separate the dry season and the wet season in each basin. As can be seen from the table, the wet season begins early (around May) across the northern basins (up to Ca River). Basins in the South and the Central Highlands (from Sesan River to Dong Nai River) have a later wet season (around July and August). Basins in the Central Coast (from Thach Han River to Kon -Ha Thanh River) have a very late and short wet season starting around August and September and lasting for just 3-4 months, which reflects the extreme weather conditions there. All series exhibit one peak per year in September or August (bold in the table) except for Huong River and Kon-Ha Thanh River whose peak times arrive later, in October and November, respectively. The lowest discharges across all basins are recorded between February and March. A serious shortage of water for hydropower dams spreads from February to April throughout the country. Although May is the start of the wet seasons in four northern basins, the discharge records in these basins are modest and the water shortage tension is still severe in other eight basins up to June/July.

**[Table 1.B.1 about here]**

Apart from the dummies for months, we added a linear time trend to the regression. All basins show a significant temporal trend after controlling for seasonality. This suggests an impact of climate change on Vietnam's river system. The highest downward trend is recorded in Da River basin, at 3.4 $m^3/s$ per month and the Sesan basin experiences the highest upward trend, at 0.78$m^3/s$. Moreover, there is an obvious contrast in the patterns: while the basins in the norther part (up to Ca River) tend to be drier over time, there is an increasing trend in the discharge of basins in the remainder. This finding is in line with Gebretsadik *et al.* (2012) but opposite to IMHEN (2010).

To analyse the timing of extreme events, we roughly defined floods and droughts as simulated flows respectively higher and lower than the mean calculated for each dam by at least one standard deviation. If discharge strictly followed normal distribution, the probability of each extreme event would be about 15.9% . However, a skew normal distribution seems to be more relevant and the probability of drought and flood within our sample are unequal, at 14% and 17.2% respectively.

Based on this classification, we calculated the average occurrences of floods by basin and by month in Table 1.B.2. A similar calculation for droughts is illustrated in Table 1.B.3. Floods in the North and the South concentrate in August and September. The peak time for flood in the Central Coast is later, between September and November. Droughts are frequent in March and April across the country. This classification of extreme events will be used later in our econometric analysis to distinguish the operation of dams against different situations of water availability.

**[Table 1.B.2 about here]**

**[Table 1.B.3 about here]**

### 1.B.2 Seasonal Mann-Kendall Test

For a more robust analysis on the discharge trend, we performed a rank-based non-parametric trend test. More specifically, we deployed the Mann-Kendall's (MK) test, which statistically detects a monotonic upward or downward trend of a variable of interest over time. Compared with parametric tests (as performed in the previous Section 1.B.1), this test has two advantages. First, it is less susceptible to outliers and extreme values. Second, it only requires a minimal assumption of specification and tolerates both linear and non-linear trend. We will apply the MK test on the yearly series first then a seasonal Kendall (SK) test (which is a modification of MK test account for seasonality) on the monthly series.

#### 1.B.2.1 Mann-Kendall Test

The test was named by Kendall (1938) and Mann (1945), who respectively proposed a statistics *tau* to measure rank correlation and presented a nonparametric test for randomness against time using the *tau* statistics. The test is based on the null hypothesis $H_0$: a series $\{x_1, x_2, \ldots, x_n\}$ comes from a population, where the random variable follows an independent and identical distribution against an alternative hypothesis $H_1$ about a monotonic trend over time (Hipel and McLeod, 2005).

The Mann-Kendall test statistics under the null hypothesis is constructed as follows:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_j - x_k); \text{ where } \begin{cases} +1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases} \tag{A5}$$

Kendall (1975) illustrated that $S$ is asymptotically normally distributed with zero mean and the variance adjusted for ties in the $x$ values:

$$\sigma_S^2 = \frac{n(n-1)(2n+5) - \sum_{j=1}^{p} t_j \left(t_j - 1\right)\left(2t_j + 5\right)}{18} \tag{A6}$$

Where $p$ is the number of tied groups in the data set and $t_j$ is the number of data points in the $jth$ tied group. As shown by Mann (1945) and Kendall (1975), a z-score constructed as follows has an approximate normal distribution even for a small value of $n = 10$:

$$z = \begin{cases} \frac{S-1}{\sigma_S} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sigma_S} & \text{if } S > 0 \end{cases} \tag{A7}$$

The order matters on the calculation of $S$ as it counts the number of times $x_j$ exceeds $x_k$ for $j > k$. The maximum possible value of $S$ occurs when $x_1 < x_2 < \ldots < x_n$, which can be calculated by:

$$D = \left[\frac{1}{2}n(n-1) - \frac{1}{2}\sum_{j=1}^{p} t_j\left(t_j - 1\right)\right]^{0.5} \left[\frac{1}{2}n(n-1)\right]^{0.5} \tag{A8}$$

The Kendall's *tau* adjusts $S$ by dividing it by $D$

$$\tau = \frac{S}{D} \tag{A9}$$

More specifically, if the ties are absent $(p = 0)$, the *tau* statistics collapses to

$$\tau = \frac{2S}{n(n-1)} \tag{A10}$$

The positive value of $S$ (or similarly $\tau$ ) indicates an upward trend and the negative sign indicate a downward trend. The zero mean of $S$ suggests that we should test whether $S$ is statistically different from zero (the null hypothesis of MK test), which is equivalent to no trend existing. The hypothesis can be tested based on the normal distribution of $z$.

We deployed the MK test on the yearly maximum, minimum and mean of discharge for each dam. As the mean series exhibit strong serial correlation, the assumption of independent and identical distribution is violated. This typically inflates the variance of $S$ statistics, and hence increasing the chance of mistakenly rejecting the null hypothesis (von Storch, 1995). To mitigate this, we followed the common practice to prewhiten all mean series by an AR(1) model before applying the test. The prewhitening procedure was not applied for the minimum and maximum series.

#### 1.B.2.2 Seasonal Kendall Test

To analyse the discharge data at a smaller time scale (monthly data), we apply a multivariate extension of the MK statistics for seasonal data with serial dependence as described by Hirsch *et al.* (1982) and Hirsch and Slack (1984). They consider a matrix $X$ comprised of a complete record (with some extensions allowing ties and missing values) over $n$ year with $m$ seasons each and the associated rank matrix $R$.

$$X = \begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,m} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,m} \end{pmatrix}; R = \begin{pmatrix} R_{1,1} & R_{1,2} & \cdots & R_{1,m} \\ R_{2,1} & R_{2,2} & \cdots & R_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ R_{m,1} & R_{m,2} & \cdots & R_{n,m} \end{pmatrix} \tag{A11}$$

The null hypothesis is that for each of the $m$ seasons, the $n$ observations are independently and identically distributed against the alternative hypothesis of a monotonic trend.

The rank of $x_{jg}$ (the $j$th data points of the season $g$th) in the case of no missing data is

$$R_{jg} = \frac{\left[n + 1 + \sum_{j=i+1}^{n} sgn\left(x_{jg} - x_{ig}\right)\right]}{2} \tag{A12}$$

The SK test computes the overall statistics $S'$ by combining each individual MK test statistics $S_g$ for each seasons. As we have 12 months, then:

$$S' = \sum_{g=1}^{12} S_g \tag{A13}$$

The statistics $S'$ is shown to be asymptotically normally distributed with zero mean and the variance is:

$$\sigma_{S'}^2 = \sum_{g=1}^{12} \sigma_g^2 + \sum_{g,h}^{g \neq h} \sigma_{gh} \tag{A14}$$

$\sigma_g^2$ is computed by:

$$\sigma_g^2 = [n\,(n-1)\,(2n+5)]\,/18 \tag{A15}$$

In our case, we used an estimate for $\sigma_{gh}$ allowing serial correlation across monthly series but no missing values:

$$\sigma_{gh} = \frac{\left[K_{gh} + 4\sum_{j=1}^{n} R_{jg}R_{jh} - n\,(n+1)^2\right]}{3} \tag{A16}$$

$$\text{where } K_{gh} = \sum_{i=1}^{n-1} \sum_{j=1}^{n} sgn\left[\left(x_{jg} - x_{ig}\right)\left(x_{jh} - x_{ih}\right)\right] \tag{A17}$$

Once the variance and the mean of $S'$ is estimated, a z-score is computed and shown to approximately follow the standard normal distribution even for a small sample with n=2. This known distribution allow us to test the hypothesis as stated at the beginning.

$$z' = \begin{cases} \dfrac{S'-1}{\sigma_{S'}} & \text{if } S' < 0 \\ 0 & \text{if } S' = 0 \\ \dfrac{S'+1}{\sigma_{S'}} & \text{if } S' > 0 \end{cases} \tag{A18}$$

The tau statistics for month $g$ is calculated as:

$$\tau_g = \frac{2S_g}{n(n-1)} \tag{A19}$$

The overall tau is the weighted average of all monthly $\tau$:

$$\tau = \frac{\sum_{g=1}^{12} n_g \tau_g}{\sum_{g=1}^{12} n_g} \tag{A20}$$

Given that we have an equal number of observations for each month and there are no missing data, the overall tau collapses to:

$$\tau = \frac{S}{6n(n-1)} \tag{A21}$$

Finally, even if the test failed to reject the null hypothesis of no overall trend, this does not necessarily mean that there is no trend at a monthly step if each month series exhibits a different (and possibly opposite) trend. To address this problem, we perform a test for a homogeneity of trend across the year against the alternative hypothesis of heterogeneous trends as suggested by Hamilton (1994).

The test is based on a statistics computed as follows:

$$Het = \sum_{g=1}^{12} z_g^2 - 12z^2 \tag{A22}$$

$$z_g = \frac{S_g - E(S_g)}{\sqrt{Var(S_g)}}; z = \frac{1}{12}\sum_{g=1}^{12} z_g \tag{A23}$$

Under the null hypothesis of no trend in any season, the statistics $Het$ approximately follows as a chi-squared distribution with 11 degrees of freedom.

#### 1.B.2.3 Results and Discussions

Table 1.B.4 illustrates the results of the MK test on the annual processes. A negative sign of the tau or z-statistic indicates a decrease in discharge while a positive sign implies an increase.

**[Table 1.B.4 about here]**

Similar to the results in Section 1.B.1, all the dams in the northern basins including Lo - Gam - Chay River, Da River, Ma River and Ca River show a downward trend. Most of the dams in other basins show an upward trend. However, only a few trends are significant. The exceptions are Nam Chien (negative, at 1% significant level), Ban Ve (negative, at 5% significant level) and Da Mi –Ham Thuan (positive, at 10% significant level).

The signs of the maximum series follow the same pattern as the mean series. In addition, there are more significant trends recorded, especially in Da River, Sesan River and Dong Nai River.

It is noted that all the minimum series of seven hydro-dams in Lo - Gam - Chay River and Da River tends to significantly decrease over time. This would create a greater pressure on power supply in Vietnam amid the dry season given that the largest hydro-dams located in Da River (Son La – 2400MW, Hoa Binh 1920 MW). Several dams in Dong Nai River basin show a significant upward trend: Tri An (400MW), Da Mi (175MW), Ham Thuan (175 MW).

The results of the SK tests on the monthly series as presented in Table 1.B.5 almost agree on the signs of trend when compared with the MK tests on the yearly series. Controlling for seasonality, the dams in Lo - Gam - Chay River and Da River again show a significantly drying trend. The significant and positive trends are found in many dams in Vu Gia - Thu Bon basin and Dong Nai River basin. While the SK tests fail to reject the hypothesis of no overall trend exists in dams located in Ma River, and Ca River, the Het p-values suggested heterogeneous trends across months. Other dams tend to follow a homogenous trend or no trend.

**[Table 1.B.5 about here]**

### 1.B.3 Stationary Test

The SK test results above suggest that many river flows to large hydropower dams in Vietnam follow a significant trend, which is either positive (dams in the south) or negative (dams in the north). We would like to discover further whether these trends include any stochastic components. In other words, can we obtain a (covariance) stationary series (those with constant mean, constant variance and covariance just depends on the temporal distance between two observations) after eliminating all the deterministic trends. Hence, the demand for some unit root tests emerge. Among them, we perform a pair of test with contradictory null hypothesises, namely Dicky-Fuller test with GLS detrending (DF-GLS) (Elliott *et al.*, 1996) and the KPSS tests (Kwiatkowski *et al.*, 1992).

#### 1.B.3.1 Logarithmization and Seasonal Standardization

As we deployed some parametric tests for stationary, which rely on linear regressions, logarithmization as guided by Hamilton (1994) was executed to better fit the normality assumption and convert any potential exponential trend to a linear trend. Furthermore, to reduce any likely influence of the seasonality of the monthly series, we seasonally standardized the series (Salas, 1993). Or more precisely, we removed the seasonality in the mean and variance:

$$x_g^* = \frac{x_g - \bar{x}_g}{\sigma_g} \tag{A24}$$

Where $x_g^*$ is the transformed value of the original observation $x_g$ and $\bar{x}_g$ and $\sigma_g$ are, respectively, the monthly mean and the monthly standard deviation of the month $g$. The series after logarithmization and/or seasonal standardization are shown in Figure 1.B.1 and Figure 1.B.2.

**[Figure 1.B.1 about here]**

**[Figure 1.B.2 about here]**

#### 1.B.3.2 Dicky-Fuller Test with GLS Detrending (DF-GLS)

The Dicky-Fuller (DF) test (Dickey and Fuller, 1979) is a popular procedure to detect a unit roots by fitting a series through an OLS estimation of a random walk model possibly including a drift or/and a (deterministic) trend. The decision on the inclusion of a drift and a trend is an empirical matter. For example, if both are included, the model is:

$$\Delta x_t = \beta_1 + \beta_2 t + (\rho - 1)\, x_{t-1} + \varepsilon_t \tag{A25}$$

Where $x_t$ is the series of interest $\beta_1$ is a drift and $\beta_2 t$ is a time trend. Regardless of the decision to include the drift and trend, the null hypothesis is $\rho = 1$, which implies the existence of a unit root or equivalently a stochastic trend.

The null hypothesis can be tested by computing a tau statistic similar to a t-statistic:

$$\tau = \frac{\hat{\rho} - 1}{Se\,(\hat{\rho})} \tag{A26}$$

where $\hat{\rho}$ is the OLS estimate of $\rho$ and $Se\,(\hat{\rho})$ is its standard error. Notably, $\tau$ does not follow the t distribution hence the critical value of the standard t-test is not valid. A table of critical value tabulated in Fuller (1976) is used instead. The null hypothesis of a unit root (non-stationary) is rejected if the absolute value of the negative tau exceeds the critical value corresponding to the chosen specification (whether to include a drift and a trend) and the chosen level of significance.

The DF test assumes that the error term $\varepsilon_t$ is white noise. To accommodate the potential serial correlation, the augmented Dickey-Fuller (ADF) test (Said and Dickey, 1984) is introduced, adding some lags of the $\Delta x_t$ and enabling ARMA error processes

$$\Delta x_t = \beta_1 + \beta_2 t + (\rho - 1)\, x_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta x_{t-i} + \varepsilon_t$$

The hypothesis is similar to the DF test. The critical value for the test is provided by Fuller (1996). The approximate p-values using the regression surface is provided by MacKinnon (1994). The selection of critical values becomes more complicated due to the decision of lag length, which is typically made based on information criteria. Ng and Perron (1994) suggests the best way to use the information criteria is to start from a high lag length then sequentially go down.

However, the ADF test is accused of size distortions and low power (DeJong *et al.*, 1992; Maddala and Lahiri, 2009; Schwert, 1989). DF-GLS (Elliott *et al.*, 1996) addresses this issue. It is based on the ADF test; however, the data is locally de-trended before testing for a unit root. The transformation of the data before the test depends on whether there is a deterministic trend or not.

Under the alternative hypotheses that $x_t$ is stationary around a linear trend, the series intercept and the trend is estimated by GLS (StataCorp, 2013):

$$\tilde{x}_t = \delta_0 y_t + \delta_1 z_t + \epsilon_t \tag{A27}$$

where

$$\tilde{x}_t = \begin{cases} x_1 & \text{if } t = 1 \\ x_t - \alpha^* x_{t-1} & \text{if } t > 1 \end{cases}$$

$$y_t = \begin{cases} 1 & \text{if } t = 1 \\ 1 - \alpha^* & \text{if } t > 1 \end{cases}$$

$$z_t = \begin{cases} 1 & \text{if } t = 1 \\ t - \alpha^*(t-1) & \text{if } t > 1 \end{cases}$$

$$\alpha^* = \frac{13.5}{T}$$

Then the OLS estimators $\hat{\delta}_0$ and $\hat{\delta}_1$ are used to remove the trend in $x_t$

$$x_t^* = x_t - \left(\hat{\delta}_0 + \hat{\delta}_1 t\right) \tag{A28}$$

Under the second alternative hypothesis that $x_t$ is stationary around a drift only, the equation to remove the trend is just $x_t^* = x_t - \delta_0$ using $\alpha^* = 1 - 7/T$.

Finally, the ADF test is applied on the de-trended series $x_t^*$ using the tabulated critical values:

$$\Delta x_t^* = \beta_1 + \beta_2 t + (\rho - 1)\, x_{t-1}^* + \sum_{i=1}^{k} \gamma_i \Delta x_{t-i} + \varepsilon_t \tag{A29}$$

In this study, we used the Ng–Perron modified Akaike information criterion (MAIC) (Ng and Perron, 2001) to choose the optimal lag length, starting from $k_{max} = floo\left\{12\left[\frac{T+1}{100}\right]^{0.25}\right\}$ as suggested by Schwert (1989).

#### 1.B.3.3 KPSS Test

The DF-GLS test sets the unit root as the null hypothesis. We used a unit root test with the null hypothesis of stationary as a confirmative test. The test with the reverse strategy chosen is the KPSS test (Kwiatkowski *et al.*, 1992).

The test assumes to decompose a series into a random walk component, ($\alpha_t$) a deterministic time trend ($\beta t$) and a stationary error term ($\varepsilon_t$)

$$x_t = \alpha_t + \beta t + \ \varepsilon_t \tag{A30}$$

where $\alpha_t = \alpha_{t-1} + \nu_t$ ; $\alpha_0 = \alpha$ and $\varepsilon_t$ and $\nu_t$ are white noise processes. The null hypothesis is that $\sigma_\nu^2 = 0$, which implies stationarity and the alternative hypothesis $\sigma_\nu^2 \neq 0$ suggests the existence of a unit root. Furthermore, under the null hypothesis, if $\beta \neq 0$, the series is trend stationary compared with the special case if $\beta = 0$, the series is stationary around a level $\alpha_0 = \alpha$.

Under the null hypothesis, the $\alpha$ and $\beta$ in case of trend stationarity or just $\alpha$ in case of level stationarity can be estimated by OLS. If we denote the residual from such a regression is $e_t$, the KPSS statistics is calculated as follows:

$$KPSS = \frac{\sum_{t=1}^{T} E_t^2}{T^2 \hat{\sigma}^2}; \qquad E_t = \sum_{i=1}^{t} e_i; \qquad t = 1, 2, \ldots, T \tag{A31}$$

where $\hat{\sigma}^2$ is a consistent estimator of the long run variance of $e_t$

$$\hat{\sigma} = \frac{\sum_{t=1}^{T} e_t^2}{T} + 2 \sum_{j=1}^{L} \left(1 - \frac{j}{L+1}\right) r_j \ and \ r_j = \frac{\sum_{s=j+1}^{T} e_s e_{s-j}}{T} \tag{A32}$$

Under the normality of the disturbance $\varepsilon_t$, the KPSS statistics is an LM statistic. The authors derived the statistics under a more general condition. The critical values of the test are estimated by simulation as tabulated in Kwiatkowski *et al.* (1992).

#### 1.B.3.4 Results and Discussions

Two major features emerge from Table 1.B.6. First, the inclusions of trends in DF-GLS test seems not to change the conclusions on the stationarity of the series. Overall, DF-GLS with a trend tends to reject the null hypothesis of unit root at a higher level of significance. Additionally, there are many disagreements between the results reported by DF-GLS and KPSS test. As the null hypothesis of these are opposites, ideally, we expect to see the rejection sign from DF-GLS test and no rejection sign from the KPSS test to conclude a series is stationary. Alternatively, we are more confident to claim the existence of a unit root in a series if the DF-GLS test does not reject its own null hypothesis but the KPSS test does. However, we quite often find the joint-rejection and sometimes joint non-rejection in Table 1.B.6. When the disagreement happens, we will favour the conclusion made by the DF-GLS test.

**[Table 1.B.6 about here]**

The DF-GLS test rejects the unit root hypothesis in most of series regardless whether a trend is included. Da Nhim is the odd one out: the specification without a trend does not reject the non-stationary hypothesis but the one with a trend does.

The Lo - Gam - Chay River and Da River basins show mixed results. For discharge to dams located there, the null hypothesis cannot be rejected even at the lowest significance level by the DF-GLS without a trend. However, the DF-GLS test with a trend changes the conclusion. Flows to Thac Ba and Nam Chien (at 5% level of significance) and to Ban Chat (at 10% level of significance) are stationary. This may suggest that the specification with a deterministic trend is more appropriate to test their stationarity. The SK test results in Table 1.B.5 confirm the existence of trends and furthermore those associated with Thac Ba and Nam Chien are shown to be more significant than Ban Chat. Four dams namely Tuyen Quang, Bac Ha, Hoa Binh and Son La cannot reject the null hypothesis of a unit root by either DF-GLS specification. There is a disagreement between KPSS test and DF-GLS for the case of the two largest dams, Hoa Binh and Son La. Including a trend the KPSS test suggests the stationarity of flows to these dams. Meanwhile there is a consensus over all models confirming the existence of a unit root in flows to Tuyen Quang and Bac Ha.

Overall, stationarity is the characteristic of the majority of the flows are investigated. However, those in the basins with a significantly negative trend detected by the SK model give cause for concern. The DF-GLS tests consistently suggest the unit root in flows to the two largest hydro-dams in Vietnam (Hoa Binh and Son La). The conclusions on the unit root in the flows to Tuyen Quang and Bac Ha is more robust, agreed upon by both the DF-GLS tests and the KPSS tests. These evidences for unit root suggest that the stochastic trends are highly likely contribute to the trend that we observe in the corresponding series.

## 1.C Appendix C: Comparing Observed Flows and Simulated Flow

### 1.C.1 Comparison Based on Statistics

#### 1.C.1.1 The Statistics

To evaluate the performance of the river flow model in general and the SWAT application in particular, a common approach is to compare the observed flow and simulated variables based on statistics established and documented prior to the modelling. There are numerous statistics constructed with various purposes. A thorough survey of these statistics can be found in Moriasi *et al.* (2007).

Besides graphical model evaluation techniques, the author divided quantitative statistics into three groups: standard regression, dimensionless and error indices. Among them, those most commonly reported in published journals are the coefficient of determination (R-squared), Nash Sutcliffe efficiency (NSE) and the bias percent (PBIAS) (Gassman *et al.*, 2007, 2014).

The coefficient of determination R-squared measures the percentage of the change in observed data explained by a best-fit regression line using simulated data as an explanatory variable. Its value is bounded between 0 and 1, and the higher it is means the better the match between observed data and simulated data. A value above 0.5 is considered as acceptable (Santhi *et al.*, 2001; Van Liew *et al.*, 2007).

Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970) is defined as the gap between a unit and the sum of the absolute squared differences between the simulated value ($Y_i^{sim}$) and observed values ($Y_i^{obs}$) normalized by the variance of the observed value

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)^2} \tag{A33}$$

where $n$ is the number of observations compared and $\bar{Y}^{obs}$ is the mean of the observed value throughout the studied period. NSE indicates how observed data and simulated data fit a 1:1 line and ranges from $-\infty$ to 1 (perfect fit). The value greater than 0 is considered as acceptable in the sense that simulated data is a better predictor of the observed data than its mean. Moriasi *et al.* (2007) also suggest some thresholds to a classify river flow model at a monthly time step: satisfactory ($0.5 < NSE \leq 0.65$), good ($0.65 < NSE \leq 0.75$), and very good ($0.75 < NSE \leq 1$).

Per cent bias (PBIAS) (Gupta *et al.*, 1999) measures the percentage the average tendency of the simulated data is larger or smaller than their observed counterparts. It can be computed by the following formula:

$$PBIAS = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right) \times 100}{\sum_{i=1}^{n} Y_i^{obs}} \tag{A34}$$

The zero value is optimal. The positive and negative values, respectively, indicate model underestimation bias and model overestimation bias. Moriasi *et al.* (2007) suggested some thresholds to classify a river flow model at a monthly time step based on the absolute value of PBIAS : satisfactory ($15 \leq |PBIAS| < 25$), good ($10 \leq |PBIAS| < 15$), and very good $0 \leq |PBIAS| < 10$).

In this study, since river flow will be used as explanatory variable, we are interested in the variation in discharge rather than its level. Hence, we mainly pay attention to a standard regression statistic, namely Pearson's correlation coefficient $r$ (Krause *et al.*, 2005; Moriasi *et al.*, 2007)

$$r = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)\left(Y_i^{sim} - \bar{Y}^{sim}\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - \bar{Y}^{obs}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i^{sim} - \bar{Y}^{sim}\right)^2}} \tag{A35}$$

This statistic measures the degree of linear relationship between two types of data, ranging from -1 (perfectly negative correlation) to 1 (perfectly positive correlation). Obviously, we should expect a good river flow model to have a positive $r$ with a magnitude near one. Unfortunately, we do not have any guide on any specific threshold to classify the fit of the model based on $r$. Hence, we report the significance at multiple levels instead (i.e., whether two variables are significantly correlated or not). Similar treatment is adopted by Giovanni (2017) to assess his GeoSFM river flow model of the Africa continent.

#### 1.C.1.2 Results and Discussions

Table 1.B.7 shows the result of our assessment. All Pearson's correlation coefficients are positive except for a negative sign for Song Con. The correlation between simulated flow to 32/40 dams and corresponding observed flow is highly significant (lower than 5% ) and quite large in magnitude. A majority of them are above 0.7. Dong Nai 4 and An Khe – Kanak only show low significance (at 10% ), while no significance is found in dams in Huong River and some in Vu

Gia – Thu Bon River.

**[Table 1.B.7 about here]**

On the other hand, 22/40 dams meet the criteria of 50% for acceptable coefficients of determination R-squared**.** All dams in Lo – Gam – Chay River, Da River, Ma River, Ca River, Thach Han River, Srepok River and Sesan River pass the test but none in Huong River and Vu Gia –Thu Bon River do.

Using the Nash-Sutcliffe efficiency, only simulated flow to Ban Chat could be classified as satisfactory and those to Hoa Binh, Song Hinh, Dai Ninh and Thac Mo could be labelled acceptable (a better predictor for observed flow than its mean).

No simulated flow could be accepted using PBIAS. This statistic shows that almost all simulated flows are overestimated (negative PBIAS). The exceptions are flows to Dak Mi 4, Song Hinh, Da Mi and Ham Thuan, which are underestimated (positive PBIAS).

There are a number of reasons why the simulated data does not perfectly match the observed data. Firstly, the model may inherit errors in data in spite of the fact that we employ the best dataset with highest resolution available. As we attempted to model rainfall-runoff on a large scale, satellite data was used in response to the shortage of consistent data. For example, the HydroSHEDS dataset is known to be exposed to error in coastal areas (Lehner, 2013) due to SRTM satellite operation characteristics (Farr *et al.*, 2007). The problem is amplified as Vietnam is a coastal country and stretches along the sea. In addition, it is particularly difficult to accurately model discharge in small, narrow costal basins like Huong River, or Thach Han River due to the strong influence of tide. In practice, previous studies modelling Vietnam's river flow on a national scale excluded these basin from analysis or did not report the assessment results there (Gebretsadik *et al.*, 2012; IMHEN, 2010).

In addition, we simulated the model with assumptions of no change in topography, soil profile and land cover. Yet such assumptions are too strong for a long period included in this study.

Notably, as it is the period when Vietnam experienced rapid economic development, the change in land cover could be considerable (for example plant shift, deforestation and urbanization). A boom of hydropower in Vietnam and countries upstream may have a considerable impact on river flow regimes and sediment patterns. However, these factors were not considered in our SWAT model due to the limit of data.

The fact that a comparison between observed flow and simulated flow to many dams produced unsatisfactory statistics is probably due to the short length of the series compared. While the simulated series is long and non-missing, some observed series (of newly built dams) is quite short (just 6 months for comparison at some dams). This could affect the performance results of the model since the statistics are ideal for a many-year comparison.

Finally, the overestimation issue systematically reported by PBIAS for almost every dam may suggest that the parameters in our SWAT model were not optimal for Vietnam given that the model is un-calibrated. An appropriate adjustment of the parameters ET, lateral flow, surface runoff, return flow and tile flow processes (Arnold, Moriasi*, et al.*, 2012) may improve the performance of the model. However, it was not executed in this study due to a shortage of longer observed flows for calibration.

Nevertheless, as we attempted to exploit the information about the variation of discharge data rather than its level, the simulated flow seem to be useful given the significantly high correlation between the two types of data. The overestimation problem could be absorbed by using appropriate dam fixed effects in future regressions using the simulated series. The above assessment also indicates that there are substantial similarities in SWAT model performance for dams in the same basin. This motivates the use of robust standard errors clustered at basin level when using the simulated data.

Finally, as river flows in later regression analysis will be pooled in order to characterize the power supply of the whole nation, a joint scrutiny could be more sensible than individual ones. The following subsection will perform some regressions to assess jointly the simulated flows to all dams.

### 1.C.2 Comparison Based on Regression

First, we perform a simple POLS regression to assess the ability of using simulated flows ($Q_{it}^{sim}$) to explain the observed flows ($Q_{it}^{obs}$).

$$Q_{it}^{obs} = \alpha + \beta Q_{it}^{sim} + \varepsilon_{it} \tag{A36}$$

Ideally, we would expect a slope ($\beta$) of one and a zero intercept ($\alpha$) in the case of perfect match between the simulation and the reality. As can be seen in the first column of Table 1.C.1, the simulated flow is far from perfect but is a highly significant predictor of the observed flows. The coefficient of simulated flows is 0.627, much larger than its robust standard error (0.0206). Together with a constant term, the variations in the simulated data explain 85% the observed data variations. A coefficient smaller than one implies that on average the simulated data tend to report a higher flow level than is observed in reality.

**[Table 1.C.1 about here]**

For a complete picture about the nexus between simulated data and observed data across different segment of the population, we employed a quantile estimator. Quantile estimator, theoretically developed by Koenker and Bassett (1978) and then (Koenker, 2005), has several advantages. Firstly, median regression (also called Least Deviations Regression), regression at the quantile 0.50, is less sensitive to influential observations than OLS. Secondly, quantile regression is more informative as it reveals the impact of explanatory variables at different points in the conditional distribution of the explained variable. Finally, as a semiparametric approach, it does not require assumptions about parametric distribution of error terms and hence is tolerant to heteroskedastic data.

A comparison across the three quartiles in Table 1.C.1 (column 2-4) reveals that higher quartiles appear with higher coefficients and higher standard errors. The median regression (the second quartile) has a coefficient of 0.551, a little bit lower than the mean regression and a higher precision. Bootstrapping slightly decreases the standard error.

Figure 1.C.1 shows that both the intercepts and the coefficients of simulated flows increase over higher quantiles. The coefficients of simulated flows range from just below 0.2 to nearly 1.0 and their confidence intervals are considerably above zero. This indicates that the simulated flows are a significant predictor regardless the level of quantile. Furthermore, there is a better fit between the simulation and reality in the higher quantiles.

**[Figure 1.C.1 about here]**

In the next stage, we include some additional variables to learn about the relationship between simulated flows and observed flows (Table 1.C.2). The baseline regression (the first column) is an OLS regression almost identical to the first column in Table 1.C.1. The only different is that Table 1.C.1 reports standard errors robust to heteroscedasticity from the "White" covariance matrix estimator (Huber, 1967; White, 1980). Meanwhile, Table 1.C.2 reports standard errors robust to heteroscedasticity and contemporaneous and lagged spatial correlation derived from the nonparametric covariance matrix estimator by Driscoll and Kraay (1998).[23] Obviously, the latter is more appropriate to our data. Because beside heteroscedasticity issue; the dependent variable is both spatially and serially correlated. Inflows to different dams, especially those within a same basin is highly likely to correlate with each other and discharge to a certain dam at a particular time is certainly not independent of its lagged values. Inferences based on just heteroscedasticity-consistent standard errors are less reliable.

**[Table 1.C.2 about here]**

The standard error of observed flow increases slightly when we depart from Column 1 of

[23]Technically, we used STATA command regress with function vce(robust) in Table 1.C.1 and command xtscc (Hoechle, 2007) with function pols in Table 1.C.2.

Table 1.C.1 (0.0206) to Column 1 of Table 1.C.2 (0.0267). The change in precision; however, does not alter the high significance of the coefficient.

Column 2 suggests the spatial consistency of our SWAT simulation performance: controlling for the location of each dam does not improve the ability to explain the observed data. In fact, the coefficients on latitude and longitude are not significant even at the 10% level and the adjusted R-squared slightly decreases when we include these redundant variables.

The operation of hydro-plants proxied by their installed capacity (column 3) or the existence of a reservoir in terms of total storage capacity (column 4) does not improve the model. The inclusion of both variables (column 5) triggers the significance at 10% of installed capacity. It is likely that the facilities and construction associated with these plants stimulate the flows to their reservoirs. However, there is no difference in the adjusted R-squared compared with the baseline model.

There is an improvement when we add month dummies to the model as the adjusted R-squared slightly increases by 0.4 percentage points (column 6). Time-invariant unobserved dam-heterogeneity (for example soil profile or topography features and other basin characteristics) matters. Controlling for them, the adjusted $R^2$ rises further to 0.856. The SWAT simulation performance seems to be consistent over time. The time trend variable added (column 8) is insignificant and fails to raise the adjusted R-squared. Adding time fixed effects besides dam fixed effects is a better choice (column 9). The model using simulated flows and controlling for both time-invariant dam –specific factors and dam-invariant time-specific factors can explain 86.5% of variations in observed flows. Then the coefficient of simulated flow marginally increases to 0.641.

It is worth discussing why the two-way fixed effect model (Column 9) is superior to the simple OLS model (Column 1). As our SWAT model was not calibrated, the parameters in the rainfall-runoff model were not optimal. Hence, the agreement between simulated and observed data depends on the heterogeneous characteristics of each subbasin (for example soil composition, land cover distribution and topographic features), which determine the sensitivity of simulated flow to the error of the SWAT parameters. Some of these characteristics are time-invariant and can be captured by dam-fixed effect. To some certain extents, the inclusion of dam-fixed effect can be considered as a simple way to "calibrate" the simulated flow for each subbasin where the dams locate. Meanwhile, time-fixed effect can absorb a part of the error terms that is consistent across subbasin but varying over time. Suppose there is an unobserved common trend in the land cover change (for example forest loss) surrounding the locations of dams, SWAT model does not account for this but the time fixed effect does. On the other hand, time fixed effect may absorb common trends over time in errors of data input to the rainfall-runoff model. For instance, the performance of satellite data on which our SWAT model relied could be varying across month of a year and across year. If it is the case, these unobserved factors will be partially handled by time fixed effects.

In Table 1.C.3, we look closer at the monthly patterns, which supplement column 6-8 of Table 1.C.2. The coefficients on the dummy variables indicate the difference in our model performance over different months compared to January. The magnitude and significance of the months depend on whether we include dam fixed effects (column 2) and a time trend (column 3). The intercepts for February to April are significantly higher than January while those of May, June and September to December are significantly higher. The difference on other months is insignificant. This suggests that the simulated flows proportionately report lower flows in dry seasons (February to April) and higher during wet seasons. This could be a consequence of monthly bias pattern in climate satellite data.

**[Table 1.C.3 about here]**

Overall, the above analysis proposes that the flow derived from the SWAT simulation is a good predictor. Using simulated flows and an intercept can explain the majority of variations in observed flows (84.9%) and such a model is both spatially and temporally consistent in the sense that we cannot improve it by controlling for location or time trends. However, the model is not robust to inter-annual variation (monthly seasonality). The introduction of dam heterogeneity and time heterogeneity improve the model a little. Nevertheless, the room for improvement is relatively small (just 1.6 percentage points) given that simulated flows contain considerable information on the variation in observed data.

**Figure 1.B.1: Logarithm of SWAT simulated flow**

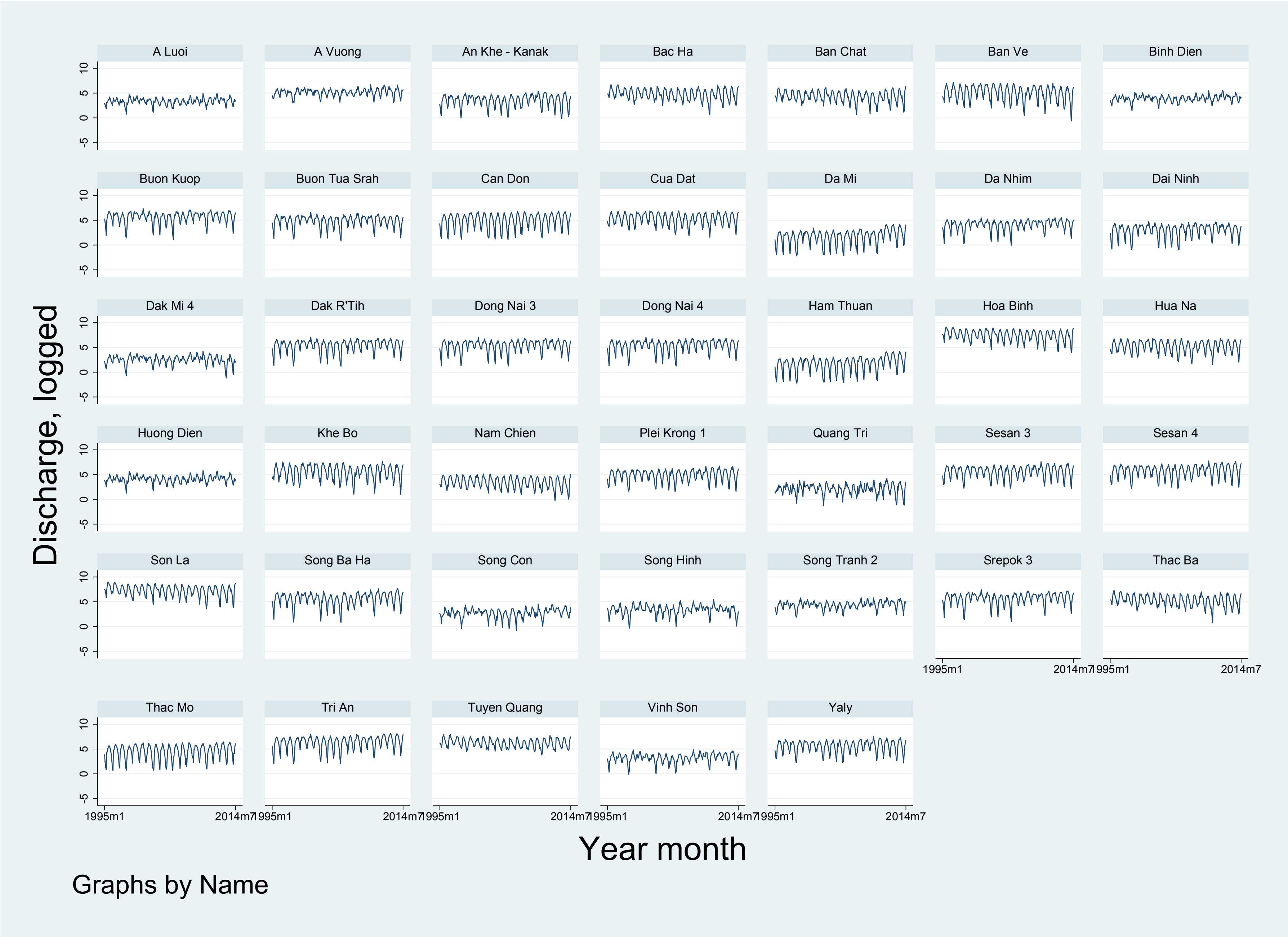


**Figure 1.B.2: Deseasonalized and logged series of SWAT simulated flows**

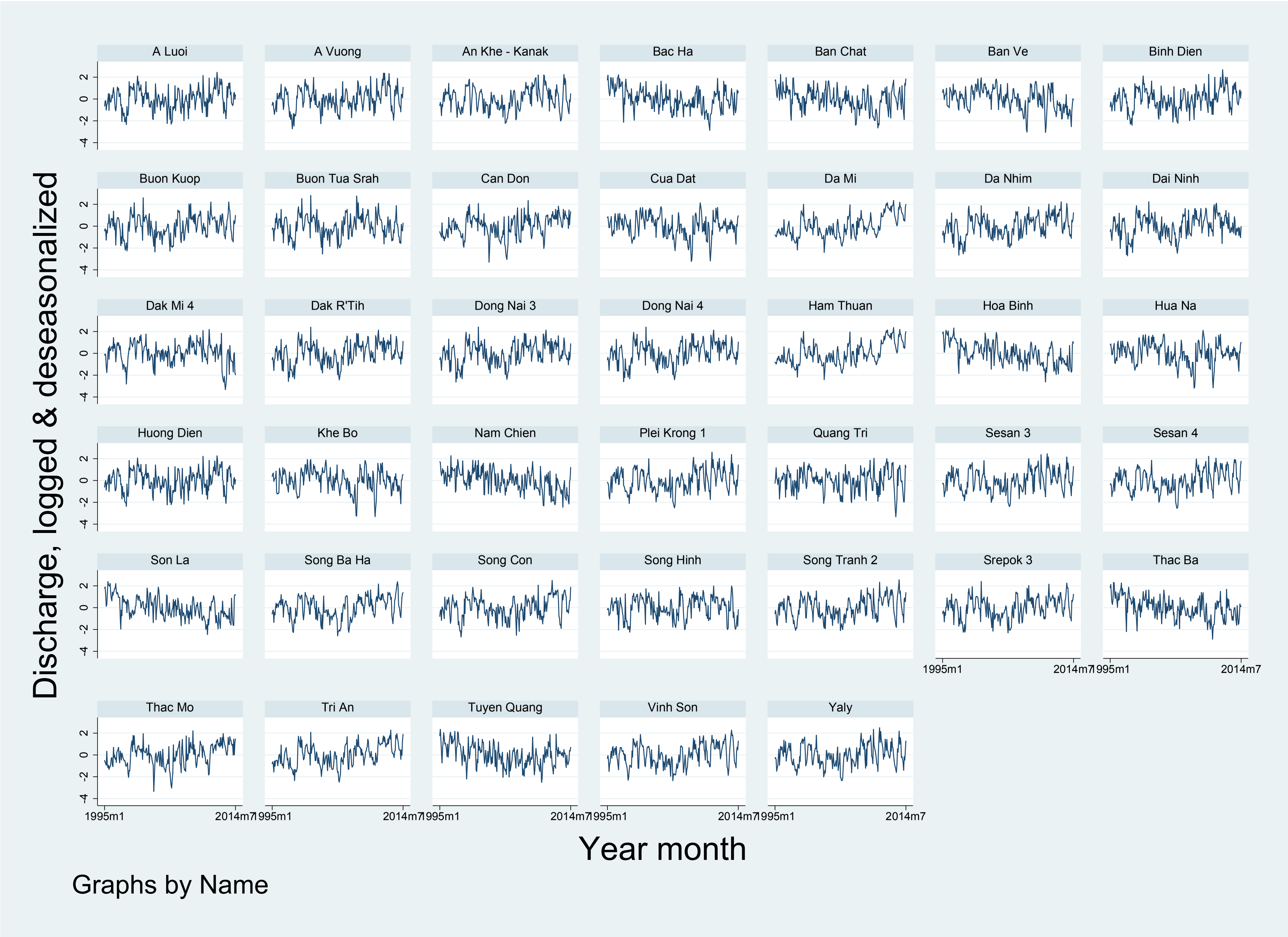
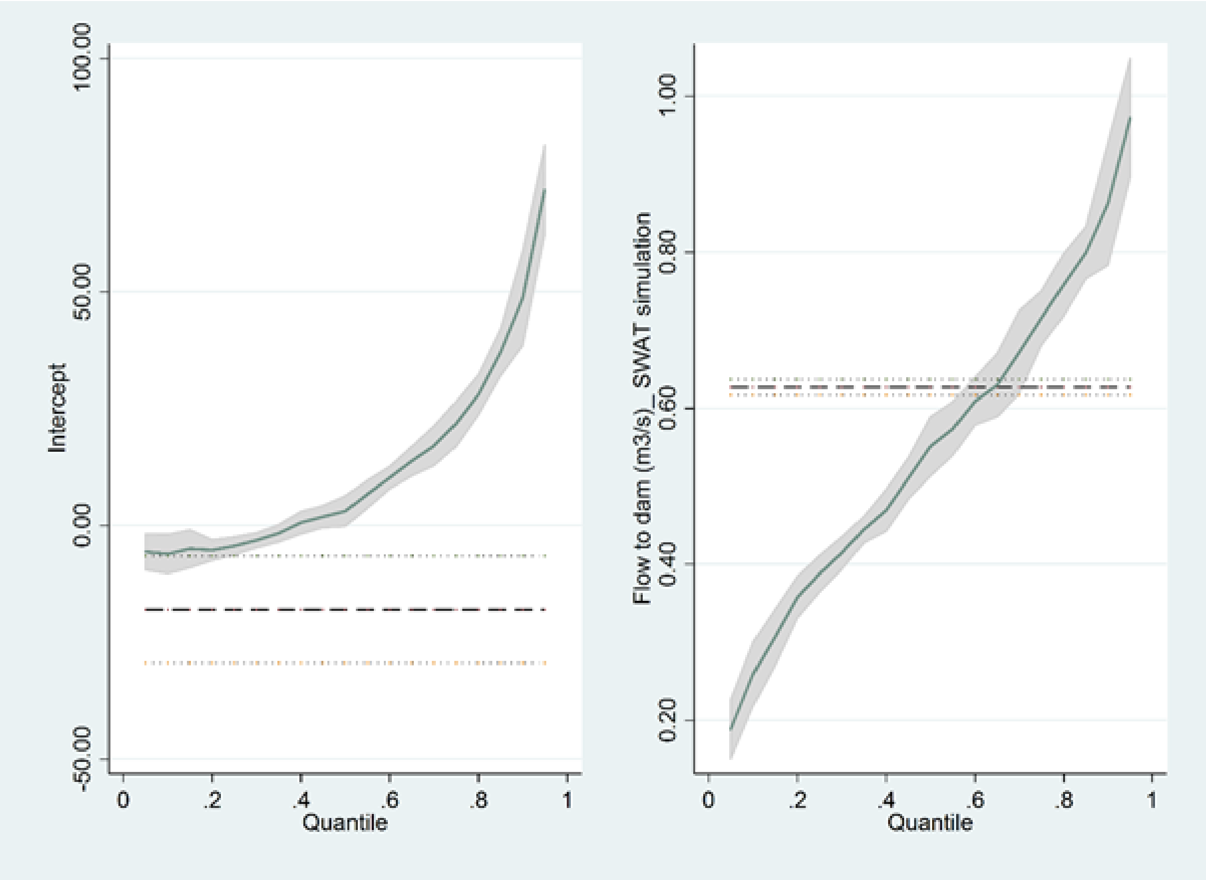


**Figure 1.C.1: Quantile regression: observed flows vs simulated flows**




Notes: Quantile regression (QR) of observed flows on simulated flows in comparison with mean regression (OLS). Blue line and horizontal dashed lines respectively indicate coefficients in QR and OLS. Confidence intervals are in grey areas (QR) or between dotted lines (OLS).

## Table 1.B.1: Seasonality and Time trend

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Lo - Gam - Chay | Da | Ma | Ca | Thach Han | Huong | Vu Gia - Thu Bon | Kon - Ha Thanh | Sesan | Ba | Srepok | Dong Nai |
| Jan | -178.5*** | -404.9*** | -200.8*** | -272.0*** | -8.329*** | -25.29*** | -51.92*** | -15.59*** | -348.5*** | -113.5*** | -167.1*** | -198.1*** |
| | (27.26) | (111.4) | (10.79) | (22.02) | (1.137) | (3.221) | (8.472) | (3.21) | (16.56) | (28.31) | (21.9) | (16.36) |
| Feb | -197.5*** | -532.4*** | -235.4*** | -303.4*** | -10.56*** | -36.08*** | -70.48*** | -25.82*** | -421.3*** | -169.5*** | -264.1*** | -258.5*** |
| | (26.14) | (104.1) | (9.506) | (20.5) | (1.169) | (3.047) | (7.597) | (2.89) | (15.67) | (23.65) | (17.98) | (14.41) |
| Mar | -205.2*** | -621.4*** | -230.9*** | -286.3*** | -11.50*** | -42.25*** | -75.92*** | -32.36*** | -442.9*** | -204.3*** | -321.9*** | -279.7*** |
| | (25.62) | (100.3) | (11.16) | (22.72) | (1.137) | (2.881) | (7.526) | (2.433) | (15.13) | (21.84) | (15.89) | (14.03) |
| Apr | -204.9*** | -605.5*** | -211.8*** | -270.6*** | -7.459*** | -36.63*** | -60.92*** | -30.36*** | -394.0*** | -203.6*** | -315.1*** | -258.7*** |
| | (26.98) | (101.3) | (14.24) | (26.45) | (1.763) | (3.335) | (8.82) | (2.823) | (15.84) | (22.14) | (17 ) | (15.46) |
| May | 38.45 | 94.09 | 36.91 | 32.1 | -1.671 | -12.53*** | -21.44 | -17.24*** | -133.8*** | -131.0*** | -165.7*** | -137.0*** |
| | (45.23) | (166.3) | (37.82) | (56.64) | (2.503) | (4.702) | (13.17) | (3.696) | (25.75) | (29.65) | (26.87) | (20.67) |
| Jun | 407.6*** | 1,023*** | 125.8*** | 212.6*** | -4.672** | -20.34*** | -17.39 | -13.78*** | -44.81 | -82.82** | -29.68 | -40.81 |
| | (67.6) | (260.3) | (31.58) | (63.17) | (1.882) | (3.701) | (13.26) | (3.918) | (27.23) | (33.68) | (27.52) | (25.34) |
| Jul | 586.2*** | 1,796*** | 235.2*** | 367.5*** | -0.46 | -18.25*** | -20.24* | -9.568*** | 74.01*** | -50.11 | 32.68 | 36.32 |
| | (71.5) | (332.9) | (25.01) | (51.12) | (2.653) | (3.175) | (12.13) | (3.424) | (28.19) | (36.42) | (27.5) | (30.1) |
| Aug | **592.3*** ** | **1,855*** ** | **410.7*** ** | **667.0*** ** | 3.623* | -8.523** | -4.498 | -2.876 | 250.3*** | 31.96 | 122.3*** | 131.0*** |
| | (82.06) | (330 ) | (27.15) | (68.73) | (1.983) | (3.607) | (13.68) | (3.293) | (34.63) | (47.43) | (29.37) | (38.28) |
| Sep | 318.7*** | 1,264*** | 366.8*** | 563.2*** | **12.34*** ** | 33.87*** | **46.95** ** | 10.55** | **417.3*** ** | **112.8* ** | **251.2*** ** | **207.3*** ** |
| | (58.13) | (265.7) | (23.16) | (54.57) | (3.041) | (7.939) | (19.34) | (4.376) | (44.37) | (59.58) | (36.44) | (42.59) |
| Oct | 141.8*** | 705.2*** | 169.1*** | 248.1*** | 7.148*** | **36.26*** ** | 36.64** | 19.73*** | 197.2*** | 112.3** | 232.4*** | 150.2*** |
| | (49.84) | (211.3) | (19.18) | (38.59) | (2.198) | (6.78) | (16.95) | (4.272) | (32.49) | (56.5) | (42.93) | (39.42) |
| Nov | -29.77 | 211.8 | -17.41 | 0.0762 | -0.215 | 30.31*** | 29.80* | **25.23*** ** | 6.877 | 93.75* | 140.9*** | 32.27 |
| | (36.64) | (165.6) | (14.33) | (29.32) | (1.562) | (7.043) | (16.51) | (7.754) | (30.22) | (56.66) | (37.16) | (31.12) |
| Dec | -123.7*** | -143.7 | -125.8*** | -162.9*** | -5.313*** | -5.274 | -24.94** | -1.012 | -227.6*** | -20.13 | -20.28 | -103.5*** |
| | (31.13) | (132.5) | (13.35) | (26.12) | (1.326) | (4.553) | (11.17) | (5.318) | (20.26) | (43.01) | (34.17) | (23.11) |
| Time trend | -0.834*** | -3.377*** | -0.235*** | -0.579*** | 0.0197** | 0.0762*** | 0.171*** | 0.0678*** | 0.777*** | 0.454** | 0.367*** | 0.523*** |
| | (0.208) | (0.826) | (0.0781) | (0.171) | (0.00856) | (0.0203) | (0.0562) | (0.0174) | (0.12) | (0.188) | (0.121) | (0.121) |
| Observations | 684 | 912 | 456 | 456 | 228 | 684 | 912 | 228 | 912 | 684 | 684 | 2,280 |
| R-squared | 0.475 | 0.26 | 0.777 | 0.657 | 0.462 | 0.411 | 0.142 | 0.572 | 0.632 | 0.156 | 0.507 | 0.19 |
| No. dams | 3 | 4 | 2 | 2 | 1 | 3 | 4 | 1 | 4 | 3 | 3 | 10 |

Notes: POLS model. Dependent variable is demeaned simulated discharge from 1995 to 2013. No constant is included. Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Dash lines separate the wet season (months with discharge above the annual mean) and the dry season (months with discharge above the annual mean).Discharge at annual high is in bold. Discharge at annual low is underlined.

**Table 1.B.2: Average flood occurences by month and by basin**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Lo-Gam | Da | Ma | Ca | Thach Han | Huong | Vu Gia - | Kon - | Sesan | Ba | Srepok | Dong Nai |
| VARIABLES | - Chay | | | | | | Thu Bon | Ha Thanh | | | | |
| Jan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Feb | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Mar | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Apr | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| May | 0.07 | 0.05 | 0 | 0 | 0.05 | 0.05 | 0.08 | 0.16 | 0.11 | 0.04 | 0.02 | 0.05 |
| Jun | 0.18 | 0.14 | 0.11 | 0.08 | 0 | 0.04 | 0.17 | 0.21 | 0.26 | 0.07 | 0.26 | 0.17 |
| Jul | 0.35 | 0.21 | 0.26 | 0.16 | 0 | 0.11 | 0.29 | 0.32 | 0.45 | 0.14 | 0.39 | 0.23 |
| Aug | **0.56** | 0.36 | 0.58 | 0.32 | 0 | 0.18 | 0.33 | **0.79** | **0.63** | 0.37 | **0.44** | 0.34 |
| Sep | 0.47 | **0.55** | **0.71** | **0.53** | 0.32 | 0.32 | 0.37 | 0.68 | 0.39 | **0.54** | 0.37 | **0.42** |
| Oct | 0.28 | 0.37 | 0.39 | 0.45 | **0.58** | 0.37 | **0.38** | 0.11 | 0.14 | 0.35 | 0.19 | 0.33 |
| Nov | 0.18 | 0.2 | 0.05 | 0.26 | 0.47 | **0.39** | 0.2 | 0 | 0.13 | 0.23 | 0.11 | 0.16 |
| Dec | 0 | 0.07 | 0 | 0.08 | 0.05 | 0.23 | 0.03 | 0 | 0 | 0.02 | 0 | 0.03 |
| Observations | 684 | 912 | 456 | 456 | 228 | 684 | 912 | 228 | 912 | 684 | 684 | 2,280 |
| N. dams | 3 | 4 | 2 | 2 | 1 | 3 | 4 | 1 | 4 | 3 | 3 | 10 |

Note: Floods are defined as monthly simulated flows at least one standard deviation higher than the mean calculated for each dam between 1995-2013. Highest occurrences are in bold.

**Table 1.B.3: Average drought occurrences by month and by basin**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Lo-Gam - Chay | Da | Ma | Ca | Thach Han | Huong | Vu Gia - Thu Bon | Kon - Ha Thanh | Sesan | Ba | Srepok | Dong Nai |
| Jan | 0.21 | 0.11 | 0.08 | 0.03 | 0 | 0.05 | 0.12 | 0.16 | 0.2 | 0.14 | 0.09 | 0.12 |
| Feb | 0.47 | 0.41 | 0.61 | 0.26 | 0.16 | 0.25 | 0.34 | 0.42 | 0.46 | 0.53 | 0.25 | 0.34 |
| Mar | **0.63** | **0.63** | **0.89** | 0.47 | 0.26 | 0.44 | **0.59** | **0.47** | **0.54** | **0.84** | **0.35** | **0.54** |
| Apr | 0.51 | 0.53 | 0.63 | **0.58** | **0.42** | **0.58** | 0.51 | 0.42 | 0.46 | 0.68 | 0.26 | 0.38 |
| May | 0.09 | 0.11 | 0.03 | 0.18 | 0.11 | 0.25 | 0.07 | 0.05 | 0.08 | 0.09 | 0 | 0.07 |
| Jun | 0 | 0.01 | 0 | 0.13 | 0.05 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0.01 |
| Jul | 0 | 0 | 0 | 0.03 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Aug | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Sep | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Oct | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Nov | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Dec | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.01 |
| Observations | 684 | 912 | 456 | 456 | 228 | 684 | 912 | 228 | 912 | 684 | 684 | 2,280 |
| N. dams | 3 | 4 | 2 | 2 | 1 | 3 | 4 | 1 | 4 | 3 | 3 | 10 |

Drought are defined as monthly simulated flows at least one standard deviation lower than the mean calculated for each dam between 1995-2013. Highest occurrences are in bold.

## Table 1.B.4: Mann-Kendall tests on annual series

| Name | Installed Capacity (MW) | Basin | Annual mean | | | Annual maximum | | | Annual minimum | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | *tau* | *z statistics* | *p-value* | *tau* | *z statistics* | *p-value* | *tau* | *z statistics* | *p-value* |
| Thac Ba | 120 | Lo - Gam - Chay | -0.28 | -1.61 | 0.11 | -0.36 | -2.1 | 0.04** | -0.52 | -3.08 | 0.00*** |
| Tuyen Quang | 342 | Lo - Gam - Chay | -0.19 | -1.12 | 0.26 | -0.26 | -1.54 | 0.12 | -0.29 | -1.68 | 0.09* |
| Bac Ha | 90 | Lo - Gam - Chay | -0.17 | -0.98 | 0.33 | -0.16 | -0.91 | 0.36 | -0.53 | -3.15 | 0.00*** |
| Hoa Binh | 1920 | Da | -0.28 | -1.61 | 0.11 | -0.51 | -3.01 | 0.00*** | -0.45 | -2.66 | 0.01*** |
| Son La | 2400 | Da | -0.24 | -1.4 | 0.16 | -0.47 | -2.8 | 0.01*** | -0.46 | -2.73 | 0.01*** |
| Nam Chien | 200 | Da | -0.42 | -2.45 | 0.01*** | -0.36 | -2.1 | 0.04** | -0.53 | -3.15 | 0.00*** |
| Ban Chat | 220 | Da | -0.1 | -0.56 | 0.58 | -0.12 | -0.7 | 0.48 | -0.5 | -2.94 | 0.00*** |
| Hua Na | 180 | Ma | -0.11 | -0.63 | 0.53 | -0.16 | -0.91 | 0.36 | -0.17 | -0.98 | 0.33 |
| Cua Dat | 97 | Ma | -0.13 | -0.77 | 0.44 | -0.16 | -0.91 | 0.36 | -0.17 | -0.98 | 0.33 |
| Khe Bo | 100 | Ca | -0.2 | -1.19 | 0.23 | -0.25 | -1.47 | 0.14 | -0.15 | -0.84 | 0.4 |
| Ban Ve | 320 | Ca | -0.36 | -2.1 | 0.04** | -0.39 | -2.31 | 0.02** | -0.25 | -1.47 | 0.14 |
| Quang Tri | 64 | Thach Han | 0.04 | 0.21 | 0.83 | 0.28 | 1.61 | 0.11 | -0.18 | -1.05 | 0.29 |
| A Luoi | 170 | Huong | 0.08 | 0.42 | 0.67 | 0.23 | 1.33 | 0.18 | 0.09 | 0.49 | 0.62 |
| Binh Dien | 44 | Huong | 0.1 | 0.56 | 0.58 | 0.23 | 1.33 | 0.18 | 0.11 | 0.63 | 0.53 |
| Huong Dien | 71 | Huong | 0.04 | 0.21 | 0.83 | 0.15 | 0.84 | 0.4 | 0.12 | 0.7 | 0.48 |
| Song Tranh 2 | 190 | Vu Gia - Thu Bon | 0.17 | 0.98 | 0.33 | 0.26 | 1.54 | 0.12 | 0.25 | 1.47 | 0.14 |
| Dak Mi 4 | 190 | Vu Gia - Thu Bon | -0.11 | -0.63 | 0.53 | 0.1 | 0.56 | 0.58 | -0.11 | -0.63 | 0.53 |
| A Vuong | 210 | Vu Gia - Thu Bon | 0.17 | 0.98 | 0.33 | 0.4 | 2.38 | 0.02** | -0.12 | -0.7 | 0.48 |
| Song Con | 63 | Vu Gia - Thu Bon | 0.08 | 0.42 | 0.67 | 0.17 | 0.98 | 0.33 | 0.1 | 0.56 | 0.58 |
| Vinh Son | 66 | Kon - Ha Thanh | 0.1 | 0.56 | 0.58 | 0.1 | 0.56 | 0.58 | 0.17 | 0.98 | 0.33 |
| Sesan 4 | 360 | Sesan | 0.25 | 1.47 | 0.14 | 0.49 | 2.87 | 0.00*** | 0.01 | 0 | 1 |
| Sesan 3 | 260 | Sesan | 0.09 | 0.49 | 0.62 | 0.46 | 2.73 | 0.01*** | -0.04 | -0.21 | 0.83 |
| Yaly | 720 | Sesan | 0.08 | 0.42 | 0.67 | 0.46 | 2.73 | 0.01*** | -0.04 | -0.21 | 0.83 |
| Plei Krong 1 | 100 | Sesan | 0.12 | 0.7 | 0.48 | 0.52 | 3.08 | 0.00*** | -0.02 | -0.07 | 0.94 |
| Song Hinh | 70 | Ba | -0.05 | -0.28 | 0.78 | -0.15 | -0.84 | 0.4 | 0.16 | 0.91 | 0.36 |
| Song Ba Ha | 220 | Ba | 0.09 | 0.49 | 0.62 | 0.33 | 1.96 | 0.05* | 0.12 | 0.7 | 0.48 |
| An Khe - Kanak | 173 | Ba | 0.05 | 0.28 | 0.78 | 0.32 | 1.89 | 0.06* | -0.1 | -0.56 | 0.58 |
| Buon Tua Srah | 86 | Srepok | -0.1 | -0.56 | 0.58 | -0.1 | -0.56 | 0.58 | 0.11 | 0.63 | 0.53 |
| Buon Kuop | 280 | Srepok | -0.03 | -0.14 | 0.89 | 0.04 | 0.21 | 0.83 | 0.16 | 0.95 | 0.34 |
| Srepok 3 | 220 | Srepok | 0.03 | 0.14 | 0.89 | 0.18 | 1.05 | 0.29 | 0.16 | 0.91 | 0.36 |
| Tri An | 400 | Dong Nai | 0.23 | 1.33 | 0.18 | 0.47 | 2.8 | 0.01*** | 0.31 | 1.82 | 0.07* |
| Da Mi | 175 | Dong Nai | 0.33 | 1.96 | 0.05* | 0.49 | 2.87 | 0.00*** | 0.37 | 2.17 | 0.03** |
| Ham Thuan | 300 | Dong Nai | 0.33 | 1.96 | 0.05* | 0.49 | 2.87 | 0.00*** | 0.37 | 2.17 | 0.03** |
| Dai Ninh | 300 | Dong Nai | -0.04 | -0.21 | 0.83 | 0.1 | 0.56 | 0.58 | 0.28 | 1.61 | 0.11 |
| Da Nhim | 160 | Dong Nai | 0.03 | 0.14 | 0.89 | 0.31 | 1.82 | 0.07* | 0.26 | 1.54 | 0.12 |
| Thac Mo | 150 | Dong Nai | 0.23 | 1.33 | 0.18 | 0.46 | 2.73 | 0.01*** | 0.32 | 1.89 | 0.06* |
| Dong Nai 3 | 180 | Dong Nai | 0.03 | 0.14 | 0.89 | 0.19 | 1.12 | 0.26 | 0.23 | 1.33 | 0.18 |
| Dong Nai 4 | 340 | Dong Nai | 0.04 | 0.21 | 0.83 | 0.2 | 1.19 | 0.23 | 0.23 | 1.33 | 0.18 |
| Dak R'Tih | 144 | Dong Nai | 0.03 | 0.14 | 0.89 | 0.23 | 1.33 | 0.18 | 0.22 | 1.26 | 0.21 |
| Can Don | 78 | Dong Nai | 0.18 | 1.05 | 0.29 | 0.43 | 2.52 | 0.01*** | 0.26 | 1.54 | 0.12 |

Series tested are the annual mean, maximum and minimum of the simulated flows.Mean series were pre-whitened by an AR1 model before the test. *** p<0.01, ** p<0.05, * p<0.1.

## Table 1.B.5: Seasonal Kendall tests for monthly series

| Name | Basin | Installed capacity (MW) | tau | z statistics | Trend p-value | Het p- value |
|---|---|---|---|---|---|---|
| Thac Ba | Lo - Gam - Chay | 120 | -0.36 | -2.4 | 0.02** | 0.3 |
| Tuyen Quang | Lo - Gam - Chay | 342 | -0.27 | -2.15 | 0.03** | 0.48 |
| Bac Ha | Lo - Gam - Chay | 90 | -0.3 | -2.04 | 0.04** | 0.71 |
| Hoa Binh | Da | 1920 | -0.42 | -2.5 | 0.01*** | 0.14 |
| Son La | Da | 2400 | -0.41 | -2.63 | 0.01*** | 0.43 |
| Nam Chien | Da | 200 | -0.36 | -2.86 | 0.00*** | 0.01*** |
| Ban Chat | Da | 220 | -0.23 | -1.94 | 0.05* | 0.51 |
| Hua Na | Ma | 180 | -0.11 | -0.93 | 0.35 | 0.01** |
| Cua Dat | Ma | 97 | -0.12 | -0.94 | 0.35 | 0.01** |
| Khe Bo | Ca | 100 | -0.1 | -0.95 | 0.34 | 0.01*** |
| Ban Ve | Ca | 320 | -0.23 | -1.71 | 0.09* | 0.03** |
| Quang Tri | Thach Han | 64 | -0.02 | -0.54 | 0.59 | 0.96 |
| A Luoi | Huong | 170 | 0.1 | 1.57 | 0.12 | 0.87 |
| Binh Dien | Huong | 44 | 0.15 | 1.8 | 0.07* | 0.73 |
| Huong Dien | Huong | 71 | 0.07 | 0.98 | 0.33 | 0.58 |
| Song Tranh 2 | Vu Gia - Thu Bon | 190 | 0.19 | 2.09 | 0.04** | 0.91 |
| Dak Mi 4 | Vu Gia - Thu Bon | 190 | -0.05 | -0.61 | 0.54 | 0.8 |
| A Vuong | Vu Gia - Thu Bon | 210 | 0.14 | 2.19 | 0.03** | 0.93 |
| Song Con | Vu Gia - Thu Bon | 63 | 0.11 | 1.02 | 0.31 | 0.54 |
| Vinh Son | Kon - Ha Thanh | 66 | 0.17 | 1.63 | 0.1 | 0.95 |
| Sesan 4 | Sesan | 360 | 0.17 | 1.58 | 0.12 | 0.89 |
| Sesan 3 | Sesan | 260 | 0.1 | 1.17 | 0.24 | 0.92 |
| Yaly | Sesan | 720 | 0.1 | 1.19 | 0.23 | 0.92 |
| Plei Krong 1 | Sesan | 100 | 0.12 | 1.55 | 0.12 | 0.9 |
| Song Hinh | Ba | 70 | 0.08 | 1.16 | 0.25 | 0.57 |
| Song Ba Ha | Ba | 220 | 0.17 | 1.33 | 0.18 | 0.57 |
| An Khe - Kanak | Ba | 173 | 0.09 | 1 | 0.32 | 0.98 |
| Buon Tua Srah | Srepok | 86 | 0.02 | 0.24 | 0.81 | 0.52 |
| Buon Kuop | Srepok | 280 | 0.13 | 1.48 | 0.14 | 0.61 |
| Srepok 3 | Srepok | 220 | 0.18 | 1.65 | 0.1 | 0.58 |
| Tri An | Dong Nai | 400 | 0.32 | 1.8 | 0.07* | 0.69 |
| Da Mi | Dong Nai | 175 | 0.37 | 1.84 | 0.07* | 0.43 |
| Ham Thuan | Dong Nai | 300 | 0.37 | 1.84 | 0.07* | 0.43 |
| Dai Ninh | Dong Nai | 300 | 0.13 | 1.16 | 0.24 | 0.22 |
| Da Nhim | Dong Nai | 160 | 0.25 | 2.13 | 0.03** | 0.82 |
| Thac Mo | Dong Nai | 150 | 0.28 | 1.35 | 0.18 | 0.12 |
| Dong Nai 3 | Dong Nai | 180 | 0.19 | 1.75 | 0.08* | 0.7 |
| Dong Nai 4 | Dong Nai | 340 | 0.21 | 1.82 | 0.07* | 0.7 |
| Dak R'Tih | Dong Nai | 144 | 0.21 | 1.84 | 0.07* | 0.71 |
| Can Don | Dong Nai | 78 | 0.23 | 1.23 | 0.22 | 0.14 |

Series tested are monthly-simulated flows. *** p<0.01, ** p<0.05, * p<0.1.

## Table 1.B.6: Stationary test for discharge series

| Name | Basin | Capacity (MW) | No trend | | | Trend | | |
|---|---|---|---|---|---|---|---|---|
| | | | Lag | DF-GLS | KPSS | Lag | DF-GLS | KPSS |
| Thac Ba | Lo - Gam - Chay | 120 | 6 | -1.18 | 1.58*** | 7 | -3.08** | .13* |
| Tuyen Quang | Lo - Gam - Chay | 342 | 7 | -1.14 | 1.22*** | 13 | -2.05 | .25*** |
| Bac Ha | Lo - Gam - Chay | 90 | 6 | -1.32 | 1.26*** | 12 | -2.07 | .19** |
| Hoa Binh | Da | 1920 | 13 | -0.48 | 1.2*** | 14 | -2.08 | 0.07 |
| Son La | Da | 2400 | 13 | -0.55 | 1.14*** | 14 | -1.97 | 0.09 |
| Nam Chien | Da | 200 | 6 | -1.23 | 2*** | 13 | -2.93** | 0.06 |
| Ban Chat | Da | 220 | 6 | -1.39 | .87*** | 6 | -2.72* | .17** |
| Hua Na | Ma | 180 | 7 | -2.56** | 0.29 | 5 | -3.75*** | .14* |
| Cua Dat | Ma | 97 | 7 | -2.53** | 0.3 | 4 | -3.96*** | .15** |
| Khe Bo | Ca | 100 | 7 | -3.26*** | 0.26 | 7 | -3.7*** | 0.09 |
| Ban Ve | Ca | 320 | 7 | -2.47** | .84*** | 7 | -3.75*** | .12* |
| Quang Tri | Thach Han | 64 | 1 | -5.99*** | 0.12 | 1 | -6.02*** | 0.1 |
| A Luoi | Huong | 170 | 12 | -2.26** | 0.21 | 3 | -4.74*** | .15** |
| Binh Dien | Huong | 44 | 12 | -2.03** | 0.32 | 3 | -4.64*** | .18** |
| Huong Dien | Huong | 71 | 12 | -2.33** | 0.13 | 3 | -4.69*** | .14* |
| Song Tranh 2 | Vu Gia - Thu Bon | 190 | 9 | -2.4** | .55** | 1 | -5.16*** | .34*** |
| Dak Mi 4 | Vu Gia - Thu Bon | 190 | 4 | -3.67*** | 0.25 | 4 | -3.68*** | .17** |
| A Vuong | Vu Gia - Thu Bon | 210 | 9 | -2.57** | 0.31 | 1 | -5.23*** | .13* |
| Song Con | Vu Gia - Thu Bon | 63 | 11 | -1.73* | 0.29 | 11 | -2.98** | .13* |
| Vinh Son | Kon - Ha Thanh | 66 | 11 | -2.34** | .45* | 11 | -2.87** | .18** |
| Sesan 4 | Sesan | 360 | 10 | -2.15** | .57** | 10 | -2.84* | .18** |
| Sesan 3 | Sesan | 260 | 10 | -2.66*** | 0.34 | 10 | -3.06** | .14* |
| Yaly | Sesan | 720 | 10 | -2.7*** | 0.33 | 10 | -3.06** | .13* |
| Plei Krong 1 | Sesan | 100 | 10 | -2.89*** | .4* | 10 | -3.11** | .13* |
| Song Hinh | Ba | 70 | 1 | -5.24*** | 0.2 | 1 | -5.32*** | .16** |
| Song Ba Ha | Ba | 220 | 12 | -1.92* | .45* | 1 | -4.88*** | .55*** |
| An Khe - Kanak | Ba | 173 | 10 | -2.23** | 0.23 | 10 | -2.93** | .13* |
| Buon Tua Srah | Srepok | 86 | 2 | -4.6*** | 0.16 | 2 | -4.75*** | .15** |
| Buon Kuop | Srepok | 280 | 2 | -4.46*** | .45* | 2 | -4.97*** | .17** |
| Srepok 3 | Srepok | 220 | 9 | -2.76*** | .4* | 2 | -4.89*** | .23*** |
| Tri An | Dong Nai | 400 | 9 | -1.82* | .88*** | 1 | -4.9*** | .34*** |
| Da Mi | Dong Nai | 175 | 3 | -2.32** | 2.16*** | 1 | -4.35*** | .59*** |
| Ham Thuan | Dong Nai | 300 | 3 | -2.32** | 2.16*** | 1 | -4.35*** | .59*** |
| Dai Ninh | Dong Nai | 300 | 2 | -3.82*** | .63** | 2 | -4.33*** | .17** |
| Da Nhim | Dong Nai | 160 | 13 | -1.63 | .57** | 2 | -4.82*** | .14* |
| Thac Mo | Dong Nai | 150 | 11 | -2.02** | .61** | 4 | -4.01*** | .25*** |
| Dong Nai 3 | Dong Nai | 180 | 13 | -2.05** | .36* | 2 | -4.62*** | .15** |
| Dong Nai 4 | Dong Nai | 340 | 13 | -2.01** | .4* | 2 | -4.66*** | .15** |
| Dak R'Tih | Dong Nai | 144 | 13 | -1.99** | .42* | 2 | -4.67*** | .16** |
| Can Don | Dong Nai | 78 | 11 | -2.18** | .49** | 4 | -4.04*** | .22*** |

Series tested are monthly-simulated flows. Optimal lag is chosen by MAIC. Max lag is 14 as suggested by (Schwert, 1989) formula. Null hypothesis of DF-GLS is non-stationary series. Null hypothesis of KPSS is stationary series. *** p<0.01, ** p<0.05, * p<0.1.

**Table 1.B.7: Performance of the un-calibrated SWAT model at different dams**

| Name | Basin | r | R-squared | NSE | PBIAS |
|---|---|---|---|---|---|
| Thac Ba | Lo - Gam - Chay | .82*** | .67* | -1.36 | -84 |
| Tuyen Quang | Lo - Gam - Chay | .8*** | .64* | -2.93 | -134 |
| Bac Ha | Lo - Gam - Chay | .78** | .61* | -1.81 | -146 |
| Hoa Binh | Da | .88*** | .78* | .25* | -58 |
| Son La | Da | .81*** | .65* | -0.44 | -65 |
| Nam Chien | Da | .98*** | .96* | -11.54 | -221 |
| Ban Chat | Da | .96*** | .92* | .51** | -59 |
| Hua Na | Ma | .92*** | .85* | -71.59 | -347 |
| Cua Dat | Ma | .75*** | .56* | -3.04 | -147 |
| Khe Bo | Ca | .83** | .68* | -28.71 | -156 |
| Ban Ve | Ca | .68*** | 0.47 | -0.65 | -57 |
| Quang Tri | Thach Han | .41** | 0.17 | -0.67 | -48 |
| A Luoi | Huong | 0.4 | 0.16 | -37.28 | -193 |
| Binh Dien | Huong | 0.19 | 0.03 | -49.96 | -379 |
| Huong Dien | Huong | 0.25 | 0.06 | -2.98 | -63 |
| Song Tranh 2 | Vu Gia - Thu Bon | 0.29 | 0.09 | -0.05 | -26 |
| Dak Mi 4 | Vu Gia - Thu Bon | 0.1 | 0.01 | -5.1 | 76 |
| A Vuong | Vu Gia - Thu Bon | .6*** | 0.36 | -62.26 | -664 |
| Song Con | Vu Gia - Thu Bon | -0.13 | 0.02 | -34.09 | -235 |
| Vinh Son | Kon - Ha Thanh | .7*** | 0.49 | -6.29 | -292 |
| Sesan 4 | Sesan | .88*** | .77* | -3.76 | -89 |
| Sesan 3 | Sesan | .54*** | 0.29 | -3.33 | -84 |
| Yaly | Sesan | .73*** | .53* | -0.9 | -59 |
| Plei Krong 1 | Sesan | .82*** | .68* | -0.31 | -64 |
| Song Hinh | Ba | .86*** | .73* | .5* | 27 |
| Song Ba Ha | Ba | .69*** | 0.48 | -5.82 | -241 |
| An Khe - Kanak | Ba | .33* | 0.11 | -6.66 | -123 |
| Buon Tua Srah | Srepok | .98*** | .96* | -0.4 | -47 |
| Buon Kuop | Srepok | .71*** | .5* | -8.84 | -177 |
| Srepok 3 | Srepok | .97*** | .95* | -2.69 | -115 |
| Tri An | Dong Nai | .82*** | .67* | -0.59 | -81 |
| Da Mi | Dong Nai | .42*** | 0.17 | -1.15 | 67 |
| Ham Thuan | Dong Nai | .53*** | 0.28 | -0.55 | 75 |
| Dai Ninh | Dong Nai | .68*** | 0.46 | .13* | -47 |
| Da Nhim | Dong Nai | .65*** | 0.42 | -10.75 | -238 |
| Thac Mo | Dong Nai | .9*** | .8* | .46* | -42 |
| Dong Nai 3 | Dong Nai | .85*** | .73* | -48.87 | -383 |
| Dong Nai 4 | Dong Nai | .35* | 0.12 | -91.82 | -401 |
| Dak R'Tih | Dong Nai | .98*** | .96* | -100.93 | -948 |
| Can Don | Dong Nai | .86*** | .74* | -3.2 | -101 |

*r*: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. R-squared: * acceptable model (Santhi *et al.*, 2001; Van Liew *et al.*, 2007). NSE: ** satisfactory model, * acceptable model (Moriasi *et al.*, 2007).PBIAS: * satisfactory model (Moriasi *et al.*, 2007).

**Table 1.C.1: Observed flows vs simulated flows –Simple regression**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| VARIABLES | OLS | QR .25 | QR .50 | QR .75 | BQR .50 |
| Flow to dam (m3/s), SWAT simulation | 0.627*** | 0.388*** | 0.551*** | 0.715*** | 0.551*** |
| | (0.0206) | (0.0128) | (0.0196) | (0.0204) | (0.0189) |
| Constant | -18.05*** | -4.391*** | 3.068** | 21.83*** | 3.068** |
| | (6.286) | (0.814) | (1.532) | (2.385) | (1.512) |
| Observations | 2,666 | 2,666 | 2,666 | 2,666 | 2,666 |
| R-squared | 0.849 | | | | |

*** p<0.01, ** p<0.05, * p<0.1.
Dependent variable is observed discharge. OLS indicates Ordinary Least Squares. QR indicates Quantile Regression. BQR indicates Quantile Regression with bootstrap standard errors and a replication number of 400. Otherwise, the robust standard errors were reported in parentheses.

**Table 1.C.2: Seasonality and Time trend**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Flow to dam (m3/s), observed data | | | | | | | | |
| Flow to dam (m3/s), SWAT simulation | 0.627*** | 0.630*** | 0.616*** | 0.622*** | 0.619*** | 0.629*** | 0.635*** | 0.634*** | 0.641*** |
| | (0.0267) | (0.0279) | (0.033) | (0.033) | (0.0338) | (0.0263) | (0.0344) | (0.0344) | (0.0373) |
| Latitude | | -0.0522 | | | | | | | |
| | | (2.184) | | | | | | | |
| Longitude | | 4.657 | | | | | | | |
| | | (6.073) | | | | | | | |
| Installed capacity (MW) | | | 0.031 | | 0.0661* | | | | |
| | | | (0.034) | | (0.0366) | | | | |
| Total storage capacity (million m3) | | | | 0.0026 | -0.0083 | | | | |
| | | | | (0.007) | (0.0071) | | | | |
| Time trend | | | | | | | | -0.268 | |
| | | | | | | | | -(0.19) | |
| Constant | -18.05** | -517.8 | -25.11** | -20.73** | -24.46** | -12.48 | -18.28** | 12.64 | -175.8*** |
| | (7.487) | (662.6) | (10.32) | (9.859) | (10.59) | (9.121) | (8.98) | (26.24) | (14.51) |
| Observations | 2,666 | 2,666 | 2,666 | 2,666 | 2,666 | 2,666 | 2,666 | 2,666 | 2,666 |
| Adjusted R-squared | 0.849 | 0.848 | 0.849 | 0.849 | 0.849 | 0.853 | 0.856 | 0.856 | 0.865 |
| Estimator | OLS | OLS | OLS | OLS | OLS | LSDV | LSDV | LSDV | LSDV |
| Dam dummies | | | | | | | Yes | Yes | Yes |
| Time dummies | | | | | | | | | Yes |
| Month dummies | | | | | | Yes | Yes | Yes | |

Driscoll-Kraay standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

**Table 1.C.3: Observed flows vs simulated flows - Monthly pattern**

| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| | Flow to dam (m3/s) observed data | | |
| Flow to dam (m3/s), SWAT simulation | 0.629*** | 0.635*** | 0.634*** |
| | (0.0263) | (0.0344) | (0.0344) |
| Feb dummy | 21.25*** | 21.72*** | 21.93** |
| | (6.409) | (8.202) | (9.245) |
| Mar dummy | 41.47*** | 42.75*** | 43.29*** |
| | (8.352) | (11.13) | (12.69) |
| Apr dummy | 42.59*** | 43.40*** | 44.14*** |
| | (8.974) | (12.28) | (14.01) |
| May dummy | -60.32*** | -61.67*** | -60.74*** |
| | (15.67) | (17.77) | (19.77) |
| Jun dummy | -89.14*** | -92.80*** | -91.46*** |
| | (25.13) | (23.06) | (23.43) |
| Jul dummy | 50.83 | 45.59 | 47.39* |
| | (34.18) | (29.03) | (28.06) |
| Aug dummy | 67.49 | 57.63 | 58.14 |
| | (47.22) | (43.51) | (42.11) |
| Sep dummy | -46.13* | -55.34* | -54.65* |
| | (25.94) | (28.79) | (29.08) |
| Oct dummy | -43.10** | -50.34** | -49.65** |
| | (18.97) | (21.85) | (22.91) |
| Nov dummy | -36.51* | -42.30** | -41.51* |
| | (19.38) | (21.01) | (21.83) |
| Dec dummy | -31.97*** | -36.54*** | -35.63*** |
| | (8.974) | (9.914) | (10.85) |
| Time trend | | | -0.268 |
| | | | (0.19) |
| Constant | -12.48 | -18.28** | 12.64 |
| | (9.121) | (8.98) | (26.24) |
| Observations | 2,666 | 2,666 | 2,666 |
| Adjusted R-squared | 0.853 | 0.856 | 0.856 |
| Dam dummies | No | Yes | Yes |
| Month dummies | Yes | Yes | Yes |

*** p<0.01, ** p<0.05, * p<0.1.
LSDV model controlling for simulated flow. Driscoll-Kraay standard errors standard errors are in parentheses. This table supplements column (6) to (8) of Table 1.C.2.

# References


Abbaspour, K. C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H. and Kløve, B. (2015), 'A continental-scale hydrology and water quality model for europe: Calibration and uncertainty of a high-resolution large-scale SWAT model', *Journal of Hydrology* **524**, 733–752.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0022169415001985*

ADB (2013), Vietnam environment and climate change assessment, Report, Asian Developement Bank.
**URL:** *http://www.adb.org/sites/default/files/institutional-document/33916/files/viet-nam-environment-climate-change.pdf*

ADB (2015*a*), Assessment of power sector reforms in viet nam - country report, Report, Asian Developement Bank.
**URL:** *https://www.adb.org/sites/default/files/institutional-document/173769/vie-power-sector-reforms.pdf*

ADB (2015*b*), Energy efficiency developments and potential energy savings in the greater mekong subregion, Report, Asian Development Bank.
**URL:** *https://www.adb.org/sites/default/files/publication/161894/energy-efficiency-savings-gms.pdf*

Alam, M. (2013), 'Coping with blackouts: Power outages and firm choices'.

Allcott, H., Collard-Wexler, A. and O'Connell, S. D. (2016), 'How do electricity shortages affect industry? evidence from india', *American Economic Review* **106**(3), 587–624.
**URL:** *http://www.aeaweb.org/articles?id=10.1257/aer.20140389*

Allen, R. G. (1986), 'A penman for all season', *Irrigation and Drainage* **112**(4), 348–368.

Allen, R. G., Jensen, M. E., Wright, J. L. and Burman, R. D. (1989), 'Operational estimates of reference evapotranspiration', *Agronomy Journal* **81**(4), 650–662.
**URL:** *http://dx.doi.org/10.2134/agronj1989.00021962008100040019x*

Arndt, C., Tarp, F. and Thurlow, J. (2015), 'The economic costs of climate change: A multi-sector impact assessment for vietnam', *Sustainability* **7**(4), 4131–4145.

Arnold, J. G. and Fohrer, N. (2005), 'SWAT2000: current capabilities and research opportunities in applied watershed modelling', *Hydrological Processes* **19**(3), 563–572.
**URL:** *http://dx.doi.org/10.1002/hyp.5611*

Arnold, J. G., Srinivasan, R., Muttiah, R. S. and Williams, J. R. (1998), 'Large area hydrologic modeling and assessement part 1: Model development', *JAWRA Journal of the American Water Resources Association* **34**(1), 73–89.
**URL:** *http://dx.doi.org/10.1111/j.1752-1688.1998.tb05961.x*

Cole, M., Elliott, R. and Strobl, E. (2014), 'Climate change, hydro-dependency, and the african dam boom', *World Development* **60**, 84.

CRED (2015), The human cost of weather related disasters (1995-2015), Report, Centre for Research on the Epodemiology of Disasters (CERD).
**URL:** *https://www.unisdr.org/2015/docs/climatechange/COP21_WeatherDisastersReport_2015_FINAL.pdf*

de Faria, F. A. M., Davis, A., Severnini, E. and Jaramillo, P. (2017), 'The local socio-economic impacts of large hydropower plant development in a developing country', *Energy Economics* **67**(Supplement C), 533–544.
**URL:** *http://www.sciencedirect.com/science/article/pii/S014098831730292X*

DeJong, D. N., Nankervis, J. C., Savin, N. E. and Whiteman, C. H. (1992), 'The power problems of unit root test in time series with autoregressive errors', *Journal of Econometrics* **53**(1), 323–343.
**URL:** *http://www.sciencedirect.com/science/article/pii/030440769290090E*

Di Luzio, M., Srinivasan, R. and Arnold, J. G. (2004), 'A gis-coupled hydrological model system for the watershed assessment of agricultural nonpoint and point sources of pollution', *Transactions in GIS* **8**(1), 113–136.
**URL:** *http://dx.doi.org/10.1111/j.1467-9671.2004.00170.x*

Dickey, D. A. and Fuller, W. A. (1979), 'Distribution of the estimators for autoregressive time series with a unit root', *Journal of the American Statistical Association* **74**(366), 427–431.
**URL:** *http://www.jstor.org/stable/2286348*

Driscoll, J. and Kraay, A. (1998), 'Consistent covariance matrix estimation with spatially dependent panel data', *The Review of Economics and Statistics* **80**(4), 549–560.
**URL:** *http://EconPapers.repec.org/RePEc:tpr:restat:v:80:y:1998:i:4:p:549-560*

Elliott, G., Rothenberg, T. J. and Stock, J. (1996), 'Efficient tests for an autoregressive unit root', *Econometrica* **64**(4), 813–36.
**URL:** *http://EconPapers.repec.org/RePEc:ecm:emetrp:v:64:y:1996:i:4:p:813-36*

EVN (2015), Report on national power system operation 2014, Report, Electricity of Vietnam.

FAO (2007), 'Digital soil map of the world'.
**URL:** *http://www.fao.org/geonetwork/srv/en/metadata.show?id=14116*

FAO (2011), Climate change impacts on agriculture in vietnam, Report UNJP/VIE/037/UNJ.

FAO (2014), 'Rivers in south and east asia (derived from hydrosheds) map'.
**URL:** *http://ref.data.fao.org/map?entryId=dc2a5121-0b32-482b-bd9b-64f7a414fa0d*

FAO (2015), 'Gaul 2015 data license'.

Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D. and Alsdorf, D. (2007), 'The shuttle radar topography mission', *Reviews of Geophysics* **45**(2).
**URL:** *http://dx.doi.org/10.1029/2005RG000183*

Fisher-Vanden, K., Mansur, E. T. and Wang, Q. (2015), 'Electricity shortages and firm productivity: Evidence from china's industrial firms', *Journal of Development Economics* **114**, 172–188.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0304387815000048*

Fuller, W. A. (1976), *Introduction to Statistical Time Series*, John Wiley & Sons, New York.

Fuller, W. A. (1996), *Introduction to Statistical Time Series*, Wiley.
**URL:** *https://books.google.co.uk/books?id=wyRhjmAPQIYC*

Gassman, P. W., Reyes, M. R., Green, C. H. and Arnold, J. G. (2007), 'The soil and water assessment tool: Historical development, applications, and future research directions', *Transactions of the ASABE* **50**(4), 1211–1250.

Gassman, P. W., Sadeghi, A. M. and Srinivasan, R. (2014), 'Applications of the SWAT model special section: Overview and insights', *J Environ Qual* **43**(1), 1–8.
**URL:** *http://www.ncbi.nlm.nih.gov/pubmed/25602534*

Gebretsadik, Y., Fant, C. and Strzepek, K. (2012), Impact of climate change on irrigation, crops and hydropower in vietnam, Report, UNU-WIDER.

Giang, P. Q., Toshiki, K., Sakata, M., Kunikane, S. and Vinh, T. Q. (2014), 'Modelling climate change impacts on the seasonality of water resources in the upper ca river watershed in southeast asia', *ScientificWorldJournal* **2014**, 279135.
**URL:** *https://www.ncbi.nlm.nih.gov/pubmed/25243206 https://www.ncbi.nlm.nih.gov/pmc/articles/PMC41*
*279135.pdf*

Giovanni, O. (2017), Power outages, hydropower and economic activity in Sub-Saharan Africa, Thesis.

Grogan, L. (2016), 'Household electrification, fertility, and employment: Evidence from hydroelectric dam construction in colombia', *Journal of Human Capital* **10**(1), 109–158.
**URL:** *http://www.journals.uchicago.edu/doi/abs/10.1086/684580*

Gupta, H. V., Sorooshian, S. and Yapo, P. O. (1999), 'Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration', *Journal of Hydrologic Engineering* **4**(2), 135–143.
**URL:** *http://ascelibrary.org/doi/abs/*

Hamilton, J. D. (1994), *Time series analysis*, Princeton University Press, Princeton.

Hansen, M., DeFries, R., Townshend, J. and Sohlberg, R. (1998), 'Umd global land cover classification, 1 kilometer'.

Hansen, M., DeFries, R., Townshend, J. and Sohlberg, R. (2000), 'Global land cover classification at 1km resolution using a decision tree classifier', *International Journal of Remote Sensing* **21**, 1331–1365.

Hao, F.-b., Zhang, X.-s. and Yang, Z.-f. (2004), 'A distributed non-point source pollution model: calibration and validation in the yellow river basin', *Journal of Environmental Sciences* **16**(4), 646–650.

Hecht, J. and Lacombe, G. (2014), The effects of hydropower dams on the hydrology of the mekong basin, Report, CGIAR Research Program on Water, Land and Ecosystems (WLE).
**URL:** *https://wle-mekong.cgiar.org/download/state-of-knowledge/hydrology-mekong-basin/Hydrology%20of%20the%20Mekong%20Basin%20_English_web%2016092014.pdf*

Hipel, K. and McLeod, A. (2005), 'Time series modelling of water resources and environmental systems'.
**URL:** *http://www.stats.uwo.ca/faculty/aim/1994Book/*

Hirsch, R. M., Slack, J. R. and Smith, R. A. (1982), 'Techniques of trend analysis for monthly water quality data', *Water Resources Research* **18**(1), 107–121.
**URL:** *http://dx.doi.org/10.1029/WR018i001p00107*

Hirsch, R. and Slack, J. (1984), 'A nonparametric trend test for seasonal data with serial dependence', *Water Resources Research* **20**(6), 727–732.

Ho, Q. B., Nguyen, H. Q. and Vo, L. P. (2013), 'Impacts of climage change on catchment flows and assessing its impacts on hydropower in vietnam's central highland region', *Global Perspectives on Geography* **1**(1).

Hoechle, D. (2007), 'Robust standard errors for panel regressions with cross-sectional dependence', *Stata Journal* **7**(3), 281–312.
**URL:** *http://www.stata-journal.com/article.html?article=st0128*

Huber, P. J. (1967), The behavior of maximum likelihood estimates under nonstandard conditions, *in* 'Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, Volume 1: Statistics', Fifth Berkeley Symposium on Mathematical Statistics and Probability, University of California Press, pp. 221–233.
**URL:** *http://projecteuclid.org/euclid.bsmsp/1200512988*

Huu, T. P. (2015), *Dilemmas of hydropower development in Vietnam: between dam-induced displacement and sustainable development*, Eburon Uitgeverij BV.

Ialy Hydropower Company (2017), 'Introduction'.
**URL:** *http://ialyhpc.vn/?php=about&basic=detail&id=240*

IFAD (2010), Vietnam environmenal and climate change assessment, Report.

IFAD (2014), Comprehensive environment and climate change assessment in vietnam, Report.

IFC (2015), Hydroelectric power: A guide for developers and investors, Report, International Finance Corporation, World Bank Group.
**URL:** *http://www.ifc.org/wps/wcm/connect/topics_ext_content/ifc_external_corporate_site/ifc+sustainability/lea*

IMHEN (2010), Impacts of climate change on water resources and adaptation measures, Report, Vietnam Institute of Meteorology, Hydrology and Climate change.
**URL:** *http://assela.pathirana.net/images/6/6e/Impact_of_climate_change_on_water_resources_and_adaptatio*

IPCC (2007), Climate change 2007 : impacts, adaptation and vulnerability : contribution of working group ii to the fourth assessment report of the intergovernmental panel on climate change, Report, Intergovernmental Panel on Climate Change.

ISPONRE (2009), Vietnam assessment report on climate change varcc, Report, Institute of Strategy and Policy on Natural Resources and Environment (ISPONRE).

Jimmy, R. W. (1969), ‘Flood routing with variable travel time or variable storage coefficients’, **12**(1).
**URL:** *http://elibrary.asabe.org/abstract.asp?aid=38772&t=3*

Kendall, M. (1938), ‘A mew measure of rank correlation’, *Biometrika Trust* **30**(1/2), 81–93.

Kendall, M. (1975), *Rank Correlation Methods*, 4th edn, Charles Griffin, London.

Khandker, S. R., Barnes, D. F. and Samad, H. A. (2009), Welfare impacts of rural electrification: A case study from bangladesh, Report, The World Bank.
**URL:** *https://elibrary.worldbank.org/doi/abs/10.1596/1813-9450-4859*

Khoi, D. N. and Suetsugi, T. (2014), ‘The responses of hydrological processes and sediment yield to land-use and climate change in the be river catchment, vietnam’, *Hydrological Processes* **28**(3), 640–652.
**URL:** *http://onlinelibrary.wiley.com/store/10.1002/hyp.9620/asset/hyp9620.pdf?v=1&t=ix0o7jx9&s=a1c1*

Koenker, R. (2005), *Quantile Regression*, Cambridge University Press.
**URL:** *http://EconPapers.repec.org/RePEc:cup:cbooks:9780521845731*

Koenker, R. and Bassett, G. (1978), ‘Regression quantiles’, *Econometrica* **46**(1), 33–50.
**URL:** *http://www.jstor.org/stable/1913643*

Krause, P., Boyle, D. P. and Bäse, F. (2005), ‘Comparison of different efficiency criteria for hydrological model assessment’, *Adv. Geosci.* **5**, 89–97.
**URL:** *http://www.adv-geosci.net/5/89/2005/*

Kumar, A. T. S., Ahenkorah, A., Rodriguez, R. C., Devernay, J.-M., Freitas, M., Hall, D., Killingtveit, and Liur, Z. (2011), Ipcc special report on renewable energy sources and climate change. chapter 5: Hydropower, Report.

Kwiatkowski, D., Phillips, P., Schmidt, P. and Shin, Y. (1992), ‘Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?’, *Journal of Econometrics* **54**(1-3), 159–178.
**URL:** *http://EconPapers.repec.org/RePEc:eee:econom:v:54:y:1992:i:1-3:p:159-178*

Le, T., Al-Juaidi, F. and Sharif, H. (2014), ‘Hydrologic simulations driven by satellite rainfall to study the hydroelectric development impacts on river flow’, *Water* **6**(12), 3631–3651.

Le, T. B. and Sharif, H. O. (2015), ‘Modeling the projected changes of river flow in central vietnam under different climate change scenarios’, *Water (Switzerland)* **7**(7), 3579–3598.

Le, T. C. and Tran, T. T. V. (2016), *The impacts of hydropower on forest, runoff and biodiveristy*, The Science and Technology Publisher, Hanoi, Vietnam, pp. 47–58.

Lehner, B. (2013), ‘Hydrosheds technical documentation version 1.2’.
**URL:** *http://www.hydrosheds.org/images/inpages/HydroBASINS_TechDoc_v1c.pdf*

Lehner, B. (2014), 'Hydrobasins technical documentation version 1.c (with and without inserted lakes)'.
**URL:** *http://www.hydrosheds.org/images/inpages/HydroBASINS_TechDoc_v1c.pdf*

Lehner, B. and Grill, G. (2013), 'Global river hydrography and network routing: baseline data and new approaches to study the world's large river systems', *Hydrological Processes* **27**(15), 2171–2186.
**URL:** *http://dx.doi.org/10.1002/hyp.9740*

Lehner, B., Verdin, K. and Jarvis, A. (2008), 'New Global Hydrography Derived From Spaceborne Elevation Data', *Eos, Transactions American Geophysical Union* **89**(10), 93–94.
**URL:** *http://dx.doi.org/10.1029/2008EO100001*

MacKinnon, J. G. (1994), 'Approximate asymptotic distribution functions for unit-root and cointegration tests', *Journal of Business & Economic Statistics* **12**(2), 167–176.
**URL:** *http://www.jstor.org/stable/1391481*

Maddala, G. and Lahiri, K. (2009), *Introduction to Econometrics*, Wiley.
**URL:** *https://books.google.co.uk/books?id=vkQvQgAACAAJ*

Mann, H. (1945), 'Nonparametric test against trend', *Econometrica* **13**(3), 245–259.

MONRE (2003), 'Vietnam initial national communication to the unfccc'.

MONRE (2009), Climate change, sea level rise scenarios for vietnam, Report, Ministry of Natural Resources and Environment (MONRE).

MONRE (2010), Vietnam's second national communication to unfccc, Report, Ministry of Natural Resources and Environment (MONRE).

MONRE (2011), Climate change, sea level rise scenerios for vietnam, Report, Ministry of Natural Resources and Environment (MONRE).

MONRE (2012), Report on national environment 2012, Report, Ministry of Natural Resources and Environment.

Monteith, J. L. (1981), 'Evaporation and surface temperature', *Quarterly Journal of the Royal Meteorological Society* **107**(451), 1–27.
**URL:** *http://dx.doi.org/10.1002/qj.49710745102*

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D. and Veith, T. L. (2007), 'Model evaluation guidelines for systematic quantification of accuracy in watershed simulations', *American Society of Agricultural and Biological Engineers* **50**(3), 885–900.

Nash, J. E. and Sutcliffe, J. V. (1970), 'River flow forecasting through conceptual models part i — a discussion of principles', *Journal of Hydrology* **10**(3), 282–290.
**URL:** *http://www.sciencedirect.com/science/article/pii/0022169470902556*

Neitsch, S., Arnold, J., Kiniry, J. and Williams, J. (2009), 'Soil and water assessment tool theoretical documentation version 2009'.

Ng, S. and Perron, P. (1994), Unit root tests arma models with data dependent methods for the selection of the truncation lag, Report, Centre interuniversitaire de recherche en économie quantitative, CIREQ.
**URL:** *http://EconPapers.repec.org/RePEc:mtl:montec:9423*

Ng, S. and Perron, P. (2001), 'Lag length selection and the construction of unit root tests with good size and power', *Econometrica* **69**(6), 1519–1554.
**URL:** *http://dx.doi.org/10.1111/1468-0262.00256*

Ngo, T. S., Nguyen, D. B. and Rajendra, P. S. (2015), 'Effect of land use change on runoff and sediment yield in da river basin of hoa binh province, northwest vietnam', *Journal of Mountain Science* **12**(4), 1051–1064.

Olivera, F., Valenzuela, M., Srinivasan, R., Choi, J., Cho, H., Koka, S. and Agrawal, A. (2006), 'Arcgis-SWAT: A geodata model and gis interface for SWAT1', *JAWRA Journal of the American Water Resources Association* **42**(2), 295–309.
**URL:** *http://dx.doi.org/10.1111/j.1752-1688.2006.tb03839.x*

PanNature (2010), 'Small and medium hydropower: Great impacts on environment but less supervision of environmental impact assessment'.
**URL:** *http://www.nature.org.vn/en/2010/07/small-and-medium-hydropower-impacts-on-environment/*

PanNature (2011), 'River basin management in vietnam: Power and challenges'.

Pham, C. H. and Pham, C. H. (2014), Project information document (concept stage) - vietnam dam rehabilitation and safety improvement project - p152309 (english), Report, World Bank Group.
**URL:** *http://documents.worldbank.org/curated/en/721261468320653018/Project-Information-Document-Concept-Stage-Vietnam-Dam-Rehabilitation-and-Safety-Improvement-Project-P152309*

Pham, V. C. (2014), 'Sustainable development of hydropower in dong nai river'.
**URL:** *http://nangluongvietnam.vn/news/vn/an-ninh-nang-luong-va-moi-truong/phat-trien-ben-vung-thuy-dien-tren-he-thong-song-dong-nai.html*

Phan, D. B., Wu, C. C. and Hsieh, S. C. (2011), 'Impact of climate change on stream discharge and sediment yield in northern viet nam', *Water Resources* **38**(6), 827–836.
**URL:** *http://download.springer.com/static/pdf/76/art%253A10.1134%252FS0097807811060133.pdf?orig*

Piman, T., Lennaerts, T. and Southalack, P. (2013), 'Assessment of hydrological changes in the lower mekong basin from basin-wide development scenarios', *Hydrological Processes* **27**(15), 2115–2125.
**URL:** *http://onlinelibrary.wiley.com/store/10.1002/hyp.9764/asset/hyp9764.pdf?v=1&t=ix0o7x3t&s=01d2*

Prime Minister (2016), 'Decision no. 428 qd/ttg: Approval of the revised national master plan for power development for the 2011-2020 period with the vision to 2030'.

Quyen, N. T. N., Liem, N. D. and Loi, N. K. (2014), 'Effect of land use change on water discharge in srepok watershed, central highland, viet nam', *International Soil and Water Conservation Research* **2**(3), 74–86.

Rossi, C. G., Srinivasan, R., Jirayoot, K., Duc, T. L., Souvannabouth, P., Binh, N. and Gassman, P. W. (2009), 'Hydrologic evaluation of the lower mekong river basin with the soil and water assessment tool model', *International Agricultural Engineering Journal* **18**(1-2), 1–13.

Saha, S., Moorthi, S., Pan, H.-L., Wu, X., Wang, J., Nadiga, S., Tripp, P., Kistler, R., Woollen, J., Behringer, D., Liu, H., Stokes, D., Grumbine, R., Gayno, G., Wang, J., Hou, Y.-T., Chuang, H.-Y., Juang, H.-M. H., Sela, J., Iredell, M., Treadon, R., Kleist, D., Van Delst, P., Keyser, D., Derber, J., Ek, M., Meng, J., Wei, H., Yang, R., Lord, S., Van Den Dool, H., Kumar, A., Wang, W., Long, C., Chelliah, M., Xue, Y., Huang, B., Schemm, J.-K., Ebisuzaki, W., Lin, R., Xie, P., Chen, M., Zhou, S., Higgins, W., Zou, C.-Z., Liu, Q., Chen, Y., Han, Y., Cucurull, L., Reynolds, R. W., Rutledge, G. and Goldberg, M. (2010), 'The NCEP Climate Forecast System Reanalysis', *Bulletin of the American Meteorological Society* **91**(8), 1015–1057.

Saha, S., Moorthi, S., Wu, X., Wang, J., Nadiga, S., Tripp, P., Behringer, D., Hou, Y.-T., Chuang, H.-y., Iredell, M., Ek, M., Meng, J., Yang, R., Mendez, M. P., van den Dool, H., Zhang, Q., Wang, W., Chen, M. and Becker, E. (2014), 'The ncep climate forecast system version 2', *Journal of Climate* **27**(6), 2185–2208.

Said, E. S. and Dickey, D. A. (1984), 'Testing for unit roots in autoregressive-moving average models of unknown order', *Biometrika* **71**(3), 599–607.
**URL:** *http://www.jstor.org/stable/2336570*

Salas, J. (1993), *Analysis and modeling of hydrologic time series*, The Mc Graw-Hill.

Santhi, C., Arnold, J. G., Williams, J. R., Dugas, W. A., Srinivasan, R. and Hauck, L. M. (2001), 'Validation of the SWAT model on a large rwer basin with point and nonpoint sources1', *JAWRA Journal of the American Water Resources Association* **37**(5), 1169–1188.
**URL:** *http://dx.doi.org/10.1111/j.1752-1688.2001.tb03630.x*

Schuol, J. and Abbaspour, K. C. (2006), 'Calibration and uncertainty issues of a hydrological model (SWAT) applied to west africa', *Advances in Geosciences* **9**, 137–143.
**URL:** *https://hal.archives-ouvertes.fr/hal-00296967*

Schuol, J., Abbaspour, K. C., Srinivasan, R. and Yang, H. (2008), 'Estimation of freshwater availability in the west african sub-continent using the SWAT hydrologic model', *Journal of Hydrology* **352**(1–2), 30–49.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0022169407007755*

Schwert, G. W. (1989), 'Tests for unit roots: A monte carlo investigation', *Journal of Business & Economic Statistics* **7**(2), 147–159.
**URL:** *http://www.jstor.org/stable/1391432*

SCS (1972), *SCS National Engineering Handbook, Section 4: Hydrology*, United States Soil Conservation Service,.
**URL:** *https://books.google.co.uk/books?id=sjOEf-5zjXgC*

Shrestha, B., Cochrane, T. A., Caruso, B. S., Arias, M. E. and Piman, T. (2016), 'Uncertainty in flow and sediment projections due to future climate scenarios for the 3s rivers in the mekong basin', *Journal of Hydrology* **540**, 1088–1104.

Srinivasan, R. and Arnold, J. G. (1994), 'Integration of a basin-scale water quality model with gis1', *JAWRA Journal of the American Water Resources Association* **30**(3), 453–462.
**URL:** *http://dx.doi.org/10.1111/j.1752-1688.1994.tb03304.x*

StataCorp (2013), 'Stata 13 base reference manual'.

The Diplomat (2016), 'China and the mekong: The floodgates of power'.
**URL:** *http://thediplomat.com/2016/05/china-and-the-mekong-the-floodgates-of-power/*

The Economist (2012), 'Lies, dams and statistics'.
**URL:** *http://www.economist.com/blogs/banyan/2012/07/mekong-river*

The Economist (2016), 'The proliferation of dams along the mekong river'.
**URL:** *http://www.economist.com/blogs/graphicdetail/2016/02/daily-chart-11*

T.Piman, Cochrane, T. A., Arias, M. E., A.Green and Dat, N. (2013), 'Assessent of flow changes from hydropower developement and operations in sekong, sesan, and srepok rivers of the mekong basin', *Journal of Water Resources Planning and Management* **139**(6), 723–732.

Tram, V. N. Q., Liem, N. D. and Loi, N. K. (2014), 'Assessing water availability in poko catchment using SWAT model', *Khon Kaen Agricultural Journal* **42**(2).

UNIDO and ICSHP (2013), World small hydropower development report 2013 - vietnam, Report, United Nations Industrial Development Organization (UNIDO) International Center on Small Hydro Power (ICSHP).
**URL:** *http://www.smallhydroworld.org/fileadmin/user_upload/pdf/Asia_South_Eastern/WSHPDR_2013_*

USGS (2015), 'Hydro1k'.
**URL:** *https://lta.cr.usgs.gov/HYDRO1K*

Van Liew, M. W., Veith, T. L., Bosch, D. D. and Arnold, J. G. (2007), 'Suitability of SWAT for the conservation effects assessment project: Comparison on usda agricultural research service watersheds', *Journal of Hydrologic Engineering* **12**(2), 173–189.

Verdin, K. L. and Verdin, J. P. (1999), 'A topological system for delineation and codification of the earth's river basins', *Journal of Hydrology* **218**(1–2), 1–12.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0022169499000116*

Vietnam National Committe on Large Dams and Water Resources Development (2006), 'Son la hydropower plant'.
**URL:** *http://www.vncold.vn/Web/Content.aspx?distid=128*

Vietnam National Committe on Large Dams and Water Resources Development (2015), 'Ban chat hydropower dam'.
**URL:** *http://www.vncold.vn/Web/Content.aspx?distid=3754*

VINACONEX (2017), 'Buon tua srah hydropower plant'.
**URL:** *http://www.vinaconex.com.vn/?id=964*

von Storch (1995), *Misuses of statistical analysis in climate research*, Springer-Verlage, New York, pp. 11–26.

Vu, M. T., Raghavan, S. V. and Liong, S. Y. (2012), 'SWAT use of gridded observations for simulating runoff – a vietnam river basin study', *Hydrology and Earth System Sciences* **16**(8), 2801–2811.
**URL:** *http://www.hydrol-earth-syst-sci.net/16/2801/2012/hess-16-2801-2012.pdf*

Vu, M. T., Raghavan, V. S. and Liong, S. Y. (2015), 'Ensemble climate projection for hydro-meteorological drought over a river basin in central highland, vietnam', *KSCE Journal of Civil Engineering* **19**(2), 427–433.

Walle, D. v. d., Ravallion, M., Mendiratta, V. and Koolwal, G. (2013), Long-term impacts of household electrification in rural india, Report.
**URL:** *https://elibrary.worldbank.org/doi/abs/10.1596/1813-9450-6527*

Wang, J. and Ishidaira, H. (2012), 'Effects of climate change and human activities on streamflow and sediment flow into the hoa binh reservoir', *Journal of Japan Society of Civil Engineers* **68**(4).

WB (2010), Economics of adaptation to climate change in vietnam, Report, World Bank.

WB (2011), Vulnerability, risk reduction, and adaptation to climate change vietnam, Report, World Bank (WB).
**URL:** *http://countryadaptationprofiles.gfdrr.org*

WB (2014), Small hydro resource mapping in vietnam : inception report, Report, World Bank Group.
**URL:** *http://documents.worldbank.org/curated/en/523501468121154457/Small-hydro-resource-mapping-in-Vietnam-inception-report*

WB and MPI (2016), Vietnam 2035 : Toward prosperity, creativity, equity, and democracy, Report, World Bank (WB) and Vietnam Misnistry of Planning and Investment (MPI).
**URL:** *http://documents.worldbank.org/curated/en/996421479825859721/pdf/103435-v2-PUBLIC.pdf*

White, H. (1980), 'A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity', *Econometrica* **48**(4), 817–38.
**URL:** *http://EconPapers.repec.org/RePEc:ecm:emetrp:v:48:y:1980:i:4:p:817-38*

Wild, T. B. and Loucks, D. P. (2014), 'Managing flow, sediment, and hydropower regimes in the sre pok, se san, and se kong rivers of the mekong basin', *Water Resources Research* **50**(6), 5141–5157.

Wooldridge, J. M. (2010), *Econometric analysis of cross section and panel data*, 2 edn, The MIT PRess, Cambridge, Massachusetts, London, England.

World Energy Council (2017), 'Hydropower'.
**URL:** *https://www.worldenergy.org/data/resources/resource/hydropower/*

# Chapter 2

# Power Outages, and Firm Performance: The Case of Vietnam

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**Chapter abstract**

We estimate the impact of power outages on firm performance in Vietnam using a framework that integrates a SWAT (Soil and Water Assessment Tool) river flow model with a hydropower generation model, and an electricity-grid-based distance interpolation technique. Potential endogeneity between economic growth, and power outages is resolved by the generation of instrumental variables based on our hydrological modelling. Comparing two waves of World Bank Enterprise Surveys (WBES) in 2005, and 2015, we find that firm performance has become more susceptible to power outages as businesses become more energy-intensive. Our results suggest that a small reduction in power interruption by 22.8 minutes per year in 2014 would increase the revenues of Vietnam's firms by 4.66 billion USD. Compared with their counterparts, firms supplied with poorer power provision are found to have lower productivity, and use less flexible input factors, which are not offset by more use of costly backup electricity generators.

> “Vietnam is a victim of its success. ”
>
> *Said by Richard Spencer, a World Bank energy specialist (2007)*

> “Planned but increasingly regular power cuts over the past month have left factories at a standstill, plunged homes into darkness and turned off traffic lights. ”
>
> *Reported by Agence France-Presse (2007)*

> “Prices need to rise sharply, but cheap power is an essential component of the party’s social contract. ”
>
> *In "A heavy load: Electrcity in Vietnam" by The Economist (2013)*

## 2.1 Introduction

In many developing countries access to a reliable source of power is essential if a country is to industrialize and grow. Firms, as large users of electricity, are particularly vulnerable to any disruption to the supply of electricity which in turn has wider welfare implications. In many countries, access to electricity remains limited while in others, although progress in electrification has been made, the consumption per head remains low. At the same time, poor supply reliability continues to hinder firm performance which impacts on the economic growth prospects of many developing countries. A good example is the case of Vietnam that has made great strides in electrification driven in part by massive investment in hydropower production such that hydropower account for between 37.6% to 40.2% installed capacity (ADB, 2011; EVN, 2015*a*,*b*). As a result, Vietnam has seen electrification rates increasing from under 2.5% in 1975 to 96% in

2009 (Min and Gaba, 2014). However, despite these considerable improvements power outages remain an ongoing problem for Vietnam's economy.

The purpose of this paper is to understand how power outages affect firm performance in Vietnam and how the impact has evolved over time, and if yes, what drives such a change. Our empirical approach is to use self-reported data for Vietnamese firms from two waves of the World Bank Enterprises Surveys (WBES) in 2005, and 2015 as well as hydropower generation data at the utility level, and spatially disaggregated data that provides information on weather, hydrography, topography, soil, vegetation, and electricity lines. One common concern with research that investigates the impact of power outages on firm performance is the endogeneity between outages and firm behaviour. To address these concerns we employ a hydro-instrumental strategy similar in nature to Allcott *et al.* (2016); Mensah (2016); Cole *et al.* (2018). More specifically, we use variations in hydropower generation due to exogenous weather shocks as an instrument for power outages. Such an approach is appropriate for Vietnam as not only does hydropower play a key role in the power mix of the country but Vietnam also has considerable variation in climate conditions and different terrains.

Our paper contributes to a growing strand of the literature that examines the impact of power outages on the economies of regions or large countries such as Sub-Saharan Africa (Mensah, 2016; Cole *et al.*, 2018), India (Allcott *et al.*, 2016; Alam, 2013), China (Fisher-Vanden *et al.*, 2015), and Pakistan (Grainger and Zhang, 2017). We examine an underexplored issues whether the requirement for power quality of an economy changes over its development path.

Vietnam represents an ideal country to study the changing dynamics in the power sector. The country has enjoyed strong economic growth and development alongside a rapid expansion of the power supply sector. However, the reliability of the power network is still patchy. Over the last 4 decades, Vietnam's growth rate averaged round 6.8% a year between 1990 and 2013 (ADB, 2015*a*), the $1.90-a-day poverty rate was reduced to under 3% (WB and MPI, 2016) and in 2008 the economy entered the group of lower-middle income countries. During this time annual power consumption has grown at double digit rates while at the same time Vietnam has almost completed the process of universal electrification with the capacity of the power system reaching 15 GW of installed capacity in 2010 (Vagliasindi and Besant-Jones, 2013).[1] However the quality of the installed electricity ranked only 113/144 countries by the Global Competitiveness Index 2012-14 (Cattelaens *et al.*, 2015). The result is that the average customer experiences between 18.10 and 39.24 power interruptions per year (equivalent to 3,134 to 8,077 minutes per year) (EVN, 2017).

In estimating the cost of power outages on firm performance, the existing literature provides a number of insights. At a more general level, there appears to be a strong (potentially non-linear) relationship between infrastructure investment, and growth (Esfahani and Ramırez, 2003; Calderón and Servén, 2004). For example, Canning and Pedroni (2008) claim that over-investment in infrastructure could reverse the net benefit of infrastructure spending as a result of resource misallocation. Second, as it is costly for firms to operate in locations where the infrastructure is poor (Lee *et al.*, 1999; Baisa *et al.*, 2010; Iimi, 2011), firms may relocate to areas or countries where the infrastructure is better (Holl, 2004). However, firms may tolerate low quality infrastructure if energy prices are subsidized. In this case, governments may pursue such a policy instead of undertaking expensive upgrades to existing infrastructure (Davis *et al.*,

[1] Since 1986 social-economic reforms (Doi moi), and energy sector reforms since 1995 have helped connect almost the entire population of nearly 100 million people to the electricity grid. Just under 2% of households remain off the grid and in 2014 just under 3% reported that their electricity needs were not being met (Ha-Minh and Nguyen, 2017).

2001). McRae (2015) offers an elegant explanation of why low-quality infrastructure, and the subsidized energy-prices may be acceptable to all economic agents (consumers, suppliers, and governments) and hence why the so-called 'subsidy trap' means an unreliable energy supply has become a persistent phenomenon in many developing countries. It is also well-documented that different types of infrastructure investment (for example transportation, ICT or dams) have different mechanisms by which they impact development (both growth and distributional effects) that are both diverse and conditional (see Allcott *et al.* (2016)).

In terms of electricity provision, the response of firms may vary. At the simplest level, an unreliable electricity supply means additional costs, for example through the need to use a backup generator (with higher unit costs of electricity). The result us that firms with limited financial resources will find it harder to access electricity-intensive sectors (Reinikka and Svensson, 2002; Adenikinju, 2003; Alby and Dethier, 2013). One consequence of increased costs is the impact on productivity (Mensah, 2016), reduced firm size (Allcott *et al.*, 2016; Grainger and Zhang, 2017), and hence lower profitability (Doe and Asamoah, 2014). As a result, firms may mitigate the impact of unreliable energy supply by switching to less energy-intensive technologies (Alam, 2013). Firms may also substitute electricity for other fuels (Allcott *et al.*, 2016) or materials (Fisher-Vanden *et al.*, 2015) (where firms outsource the production of intermediates instead of making them in house).

Despite power outages being intuitively costs, it is not easy to quantify the economic consequences of power outages, especially within a fast-growing economy context. As previously suggested, there are a number of potential endogeneity concerns. These include measurement error (Allcott *et al.*, 2016), selection bias (Alam, 2013), and simultaneity between firm performance and power reliability (Steinbuks, 2011; Fisher-Vanden *et al.*, 2015; Allcott *et al.*, 2016).

The simultaneity issue is further complicated in our case due to the dual role played by economic growth. On the one hand, growth generates taxable income that can be used to develop the power sector, but on the another hand, growth can lead to additional demand for power which could impact reliability. It is usually the case that long lag times in construction of new infrastructure means that governments are chasing to catch up with demand leading to fall in reliability. Under such circumstances, the causal relationship between power provision and firm performance is difficult to identify in the absence of a proper treatment of endogeneity concerns.

A key difference between our study and others that employ a hydro-IV approach is that they have tended to investigate multiple-grid cases (different countries or states within a large country that use different electricity grids). In this case access to different grids can help explain the variation in firm level power provision. In our case, our instrument is constructed by matching firms with (hydro)power plants that are connected to the same grid. Because we are dealing with the case of a single-grid (i.e. all firms, and utilities connect to a same centrally managed grid within a small country), and have limited information on the distribution rule (if any) this presents several challenges. First, because of the interconnected system it is difficult to match the power provision of a firm to particular large hydropower plant(s) as the impact of reduced electricity production could be nationwide. Second, fossil fuel power plants are connected to the system and can be used to increase power supply when hydropower plants reduce production as a result of bad weather. Our solution is to take an interdisciplinary approach and use a rainfall-runoff model based on Soil and Water Assessment Tool (SWAT) to simulate river flows to the 40 largest hydropower dams across Vietnam. This allows us to take into account a variety of terrain conditions and variation in the weather. The simulated series from the SWAT model are then used as a key predictor of hydropower generation to eliminate the component of electricity production that is driven by changes in demand. The estimated series from the generation model are then used to construct an index for the weighted hydro-plant factors that are explained by the exogenous variations in hydrological conditions, using a grid-based distance penalty parameter calibrated by the 'reduced-form equation' of the IV estimation. Finally, the hydro-index is used as a single instrument for power outages measured in multiple dimensions in the 'structural equation' to address the endogeneity concerns.

To summarize, the contribution of this paper is three-fold. First, we contribute to the hydro-IV literature by integrating river flow modelling with a firm level dataset for a fast growing single gridded country. Second, we estimate the impact of power outages on the performance of firms in a rapidly growing country, where potential endogeneity issues are likely to be more of a concern than in countries with limited changes in demand. Third, to the best of our knowledge, we are the first to show that the need to upgrade power provision changes over time and is conditional in part on the complexity of the production process.

To briefly summarize our results, we find that the impact of power outages on firm performance is relatively small but became more important in the later period as firms increased their dependency on electricity. In 2015 we find a significant reduction in revenue of between 0.73% to 1.81% in response to a 1% increase in power outages. In other results we find that frequent outages are found to cause larger losses than a small number of long-lasting outages.

The remainder of the paper is organised as follows. Section 2 provides some background information on Vietnam's power sector. Section 3 sketches a theoretical model, and describes our testable hypotheses. Section 4 presents our empirical strategy, describes our dataset and provides the OLS estimates. Section 5 details our instrumental strategy, with the results shown in Section 6. Section 7 concludes.

## 2.2 The Power Sector and Power Reliability in Vietnam

Between 2004 to 2014, Vietnam succeeded in more than tripling its power capacity from 10.8 GW to 34.1 GW in response to a sharp increase in demand that grew rapidly from 41.2 TWh to 128.63 TWh (ADB, 2015*a*; EVN, 2015*a*,*b*). Electrification was almost complete by 2014 with only 2% of the population still without access to electricity compared to around half of the population in 1995 (ADB, 2015*a*). At the same time, consumption per head of the clean power went up almost tenfold from 156 kWh in 1995 to 1,415 kWh in 2014 (ADB, 2015*b*). In 2004 this demand was supplied primarily by a combination of hydropower and natural gas. While the share in the national installed capacity of hydropower increased from 37.6% to 40.2%, the share supplied by natural gas was reduced from 28.5% to 21.5%. The remaining demand was satisfied through an increase in the share from coal that increased substantially from 11.5% to 28.7% and a small contribution from oil with its share increasing from 1.8% to 3.5%. Towards the end of the period small hydropower emerged as a contributor to the power sector and accounted for 5.2% of capacity. Finally, other renewable sources make up just 0.2% of the total installed capacity. Notably, during this period the economy moved from self-sufficiency in electricity prior to 2004 to a net electricity importer with the balance exceeding 6.54% of its consumption at the peak of Vietnam's energy supply crisis in 2010 before falling to 3.3% in the final two years of our time period.[2] In terms of demand, the industrial sector was the largest consumer, accounting for 41.8% of consumption in 2004 rising to 53.87% in 2014. The share

[2] Author's own calculations from U.S. Energy Information Administration (2017).

of consumption of households fell from 42.9% to 35.58% over the same period. Services and agriculture consumed far less electricity, accounting for just under 5%, and 2% of consumption, respectively.

One challenge that we face is that data on power quality in Vietnam is limited, especially for the earlier years. According to Vagliasindi and Besant-Jones (2013), between 2005-2008, the average SAIFI (System Average Interruption Frequency Index) varies between 2, and 12 interruptions per customer.[3] As self-reported by EVN (2017), the period between 2012 and 2014 saw a sharp improvement in power quality, with the SAIDI (System Average Interruption Duration Index) falling from 8,077 to 3,134 minutes/customer, SAIFI falling from 39.24 to 18.10 times per customer, and MAIFI (Momentary Average Interruption Frequency Index) falling from 5.07 to 2.63 times per customer.[4]

Despite the increase in the reliability of the power supply there remains room for improvement. For example Vietnam's power reliability in 2014 (SAIFI=18.10; SAIDI=3,134) compared to a SAIFI of 0.86-1.33, and a SAIDI of 86-159 for North America (IEEE Working Group on Distribution Reliability, 2015). The quality of Vietnam's electricity provision is ranked 113/144 by the Global Competitiveness Index 2012-14 with performance particularly poor in rural areas (Cattelaens *et al.*, 2015). Vietnam's Getting Electricity Indicator is ranked 130 out of 190 countries in *Doing Business* as evaluated by the World Bank in 2014 (EVN, 2017).

A number of arguments have been made to explain the deficiencies in the power supply

[3]SAIFI indicates the average number of interruptions that a customer would experience.

[4]SAIDI indicates the average outage duration for each customer served while MAIFI indicates the average number of momentary interruptions (outages of less than 5 minutes in length) that a customer would experience during a given period (typically a year).

in Vietnam. The most frequently cited explanation given by EVN is hydrology uncertainty. The prominent role of hydropower in the energy mix means that the reliability of the system largely depends on hydrological conditions which in turn are driven by changes in the weather. As we shall show, although the operation of large reservoirs partially reduces this source of variation, there remains a substantial effect. A second reason for power shortages, and common to developing countries, is system overload, which refers to the situation when demand exceeds the capacity of the delivery system due to spikes in demand at certain times of the day or year (Carranza and Meeks, 2016). While fluctuations in either weather or demand are difficult to predict, they are subject to regular seasonality, and cycles. However, the existence of power outages suggests a lack of investment in existing and new power infrastructure.

Turning to electricity pricing in Vietnam, we know that the electricity tariff is regulated by the government in order to maintain a low prices primarily as a way to reduce poverty and as part of an industrial strategy and to attract foreign investors. Despite recent tariff reforms, the average tax-included electricity selling price was 1,622 VND/kWh (approximately 7.5 US cents/kWh), which according to Cattelaens *et al.* (2015) is still lower than the cost of production. As a result, the power market is not an attractive investment opportunity which means that funding from the state via state-owned companies, especially EVN and its subsidiaries, plays a decisive role in the expansion of energy supply sector in Vietnam. Although state investment was sufficient when Vietnam was first developing, it has not able to keep up with demand. Furthermore, investment by EVN, which used to be a monopoly, has often been criticized for being wasteful, ineffective, and for impeding the development of new energy sources to fill in the gap in demand (UNDP, 2010).

In addition to problems with generation, problems with transmission, and distribution have contributed to power unreliability in Vietnam. A low automation rate, inconsistent management of the power network, and grid maintenance has reduced the efficiency of the system (Cattelaens *et al.*, 2015). Although network power losses are reported to has fallen from 11.05% (2006) to 8.6% (2014), these compare with the rate of 7% in Germany (Cattelaens *et al.*, 2015).[5]

## 2.3 Theoretical Framework and Testable Hypotheses

### 2.3.1 Theoretical Model

Our theoretical framework follows Allcott *et al.* (2016). To briefly summarize, assume firms use a technology defined by a Cobb Douglas function with 4 inputs (capital $K$, labor $L$, electricity $E$, and materials $M$) that generates revenue $R$ with a price set by the perfectly competitive market $p$ given by:

$$R = p.Q = p.A.K^{\alpha_K} L^{\alpha_L} M^{\alpha_M} E^{\alpha_E} = \Omega.K^{\alpha_K} L^{\alpha_L} M^{\alpha_M} E^{\alpha_E} \tag{2.1}$$

where $\alpha_F$ is the intensity of factor $F \in \{K, L, M, E\}$, Q is the physical output, A is the physical productivity (TFP) and $\Omega = p.A$ is the revenue productivity (TFPR). Investment in capital $K$ is assumed to be fixed, and totally sunk prior to production. Labour $L$ is partially flexible but can only be adjusted at the beginning of each year, conditional on a firm's prior belief about the probability of power outages. Material inputs are assumed to be fully flexible during the production process and can be adjusted conditional on the occurrence of a power disruption happening. Yearly revenue is given by the accumulation of daily revenues, and for each day

[5]Power outages may also be caused by accidents. For example in May 2013, the 500 kV North-South lines were hit by a falling tree. The accident interrupted the transmission, and distribution, and led to a collapse of the power system due to large deficit of power causing a loss of 9,400 MW in installed capacity from 43 generators in the South Vietnam and leaving 8 million customers off-grid over 1-8 hours (Son and Voropai, 2015).

power outages may occur with a probability $\delta$. A firm decides the level of inputs of materials and electricity at the point where their marginal revenue products equals their prices. Without a power outage, the marginal revenue product of electricity equals the cost to purchase electricity from the grid $p_E$. When a power outage occurs, the firm faces a higher electricity price ($p_G > p_E$ for firms that have a generator, and $p_S = \infty$ for firms that do not have a generator). Therefore, during an outage, generator-owners use less electricity, and non-generator-owners shutdown (do not consume any electricity). The effect of a higher price of electricity incurred during a power outage is to lower the marginal revenue product of material inputs, and the yearly expected marginal revenue product of labor. Consequently, a firm will reduce its inputs of materials, and labour, which Allcott *et al.* (2016) calls 'input tax' effects. Meanwhile, power outages also lower productivity (measured TFPR) as all inputs except those that are fully flexible (material inputs and electricity) are wasted during periods of power outage.

### 2.3.2 Testable Hypotheses

Based on this simple theoretical framework, we derive 5 testable and related hypotheses. Everything else equal, we hypothesis that a firm that has access to a less reliable electricity supply tends to:

1. Hypothesis 1: Generate less revenue,
2. Hypothesis 2: Have lower productivity,
3. Hypothesis 3: Use less flexible inputs (electricity, labor and material inputs),
4. Hypothesis 4: Self-generate more electricity through the use of a generator.

5. Hypothesis 5: Have a revenue gap that is wider than the productivity gap as the former is driven by the combination of the latter, and the reduction in input usage.

## 2.4 Data and Empirical Strategy

### 2.4.1 Empirical Specification

To evaluate the impact of power reliability on the operation of firms, we estimate the following regression:

$$y_{ijpt} = \alpha + \beta.Outage_{ijpt} + \Pi'.FIRM_{ijpt} + \Sigma'.PROVINCE_{pt} + \theta_{jt} + \varepsilon_{ijpt} \tag{2.2}$$

where $i$, $j$, $p$, and $t$ are subscripts for firm, sector, province, and year, respectively. The dependent variable $y_{ijpt}$ is a measure of the performance or factor inputs (in log form) of firm $i$ in sector $j$ located in province $p$, and surveyed in year $t$. Finally, $Outage_{ijpt}$ is a measure of the quality of power supplied to that firm, which could be one of three variables: power outage frequency, intensity or volume (in log form). The intercept is $\alpha$, and $\beta$ is our parameter of interest. $FIRM_{ijpt}$ is a vector of firm characteristics including size, age, ownership, legal status, foreign trade activities, a measure of financial constraint, and corresponds to the vector of coefficients $\Pi$. $PROVINCE_{pt}$ is a vector of province specific variables (in the given year) including the average elevation, cooling degree, rainfall shocks, province industrial product (IP) share, and province IP growth. This vector corresponding to the vector of coefficients $\Sigma$. $\theta_{jt}$ is sector-year dummies, and $\varepsilon_{ijpt}$ is the idiosyncratic error term. Equation 2.2 is estimated for each individual survey ($t$ = 2005, 2015).

### 2.4.2 Data and Summary Statistics

#### 2.4.2.1 Firm-level Data

Our firm level data comes from the World Bank Enterprise Surveys (WBES) that includes a range of questions on infrastructure and firm performance.[6] The WBES data are collected from interviews with owners/ top managers of registered companies in the manufacturing, and services sectors with at least 5 employees. For Vietnam, there were 3 surveys that were undertaken in 2005, 2009, and 2015. Each WBES survey records firm-level data for the previous fiscal year. Hence, the 2005, 2009, and 2015 surveys capture the business environment and firm performance indicators for the years 2004, 2008, and 2014, respectively. In this paper we use the 2005 and 2015 surveys.[7]

**Firm characteristics.** As our study includes a spatial dimension it is important to have firm location information. We choose the province as the spatial unit of analysis based on an administrative GIS map for 2005. To account for the expansion of the capital city (Hanoi) after 2008, all centroid-based variables for firms in Hanoi in Survey 2015 were constructed using weights for the old Hanoi area, and the former Ha Tay area computed from their industrial values just

[6]The WBES covers 127 thousands firms across 139 countries and also asks questions on finance, corruption, crime, competition, labor, obstacles to growth. The WBES has been operating since the 1990's, and has been run from the Enterprise Analysis Unit (EAU) since 2005-06.

[7]We exclude the 2009 survey as the 2007-2008 financial crisis means that the 2008 firm level characteristics are less reliable. In additon, power outages in 2008 were in the main driven by failures to operate planned power sources which means our hydro-IV strategy would not be able to capture shocks.

before the expansion.[8] We redefine sector, and size variables using variables collected from the face-to-face interview phase of the WBES surveys.[9] A series of variables were created to control for firm heterogeneity, including sector dummies (based on the first two digits of the main product ISIC (International Standard Industrial Classification) code), four size dummies, a firm age variable, four dummies for state and foreign ownership at the 10%, and 50% thresholds, a share-holding dummy, a publicly quoted company dummy, a dummy for access to credit, and an exporter dummy. For more details on the original variables, treatments for missing values, and the data cleaning process see Appendix 2.A.1.

**Power supply provision.** We use two variables to measure the frequency and intensity of power outages (the average number of power outages per month, and the typical duration of an outage). To analyze the impact of both factors we create a variable that proxies power outage volume (hours per month), calculated as the product of power outage frequency (occurrences per month), and power outage intensity (hours per occurrence).[10] We construct a variable for generator usage as a percentage of electricity used, and assign a zero value for those firms that do not own or share a generator. See Appendix 2.A.2 for details.

**Firm performance.** Monetary variables (revenues, and input variables including the replacement value of machinery, vehicles, and equipment (proxied for capital stock); materials cost; labor cost; fuel cost; electricity cost, and energy cost) are deflated using the World Bank defla-

[8] In 2007 industrial gross output at current prices for Hanoi and Ha Tay are 116,096.4, and 20,173.5 (billion VND), respectively. The weight applied is 1:0.1737. We ignore the rural areas that used to belong to Hoa Binh, and Vinh Phuc provinces, and latter appended to Hanoi due to their limited economic importance.

[9] The surveys were designed as a two-stage procedure. The variables in the first stage (screening by phone) include sector and size are and considered less reliable than those collected in the second stage (face-to-face interview with firm owners/managers).

[10] The three proxies for power quality were log transformed after being added to 1 (to address the log of zero problem).

tors and then logged (base year 2010=100). The energy cost variable is only available for 2005 Survey, and the electricity, and fuel cost variables are only available for the 2015 Survey. To reduce the impact of outliers we apply the 'three sigma rule' to account for extreme values in the revenue and factor input variables.[11] We also estimate two total factor productivity revenue (TFPR) variables based on YKL, and YKLM models (Details of how we measure the efficiency of input usage are given in Appendix 2.A.3).

#### 2.4.2.2 Province-level Data

It is possible that certain characteristics of a province may simultaneously affect firm performance and power provision. We construct two variables to control for economic conditions at the province level based on data from the *Statistical Yearbooks of Vietnam* by Vietnam's General Statistics Office (GSO).[12] Province industrial product (IP) share is calculated as the ratio of the gross industrial output of each province, and national gross industrial output for each year and is a proxy for agglomeration economies and also captures the importance of each province to the national economy. We argue that this variable may affect both firm performance and the priority that may be given to power distribution when there are shortages (priority given to areas of strategic economic importance). Second, we calculate a Province IP index to capture IP growth at the province level that could both improve a firm's performance but worsen power reliability if power supply significantly lags demand.[13]

We also control for topography differences. In general, we hypothesis that less elevated

[11] We calculate the mean, and the standard error of the log of firm revenue for each year in the original database then define 'extreme values' as those that more than three standard errors deviations from the mean. A similar process is applied for factor input variables.

[12] Data is accessible at http://www.gso.gov.vn/Default_en.aspx?tabid=515.

[13] See Appendix B1 for details

provinces offer better conditions for business (i.e. better transportation and access to the sea ports). However, they may also be more susceptible to electricity interruptions caused by an overloaded system. On the other hand, highly-elevated provinces may be in a less favourable position for the maintenance, and upgrade of power grids, and other distribution, and transmission facilities, which may be another cause of unreliability in the power sector. To control for elevation we use the void-filled DEM from the HydroSHEDS database to calculate the mean elevation of each province where the boundaries are defined by the GAUL dataset.[14]

In addition to elevation we also include controls for temperature that can both affect power provision (hot weather increases electricity demand for air-conditioners, and hence is more likely to cause a system overload) and firm performance (that could for example negatively affect labor productivity). Following the literature, we control for cooling degree (Allcott *et al.*, 2016) which is derived from the forecast variable of air temperature at 2m extracted from a gridded temperature data set (NCEP-DOE Reanalysis 2 provided by the NOAA/OAR/ESRL PSD). See Appendix 2.B.2 for more details about spatial interpolation and computation methods.

Previous studies suggest that rainfall shocks can affect the economy through multiple channels other than through its effect on hydropower generation. For example, more rain may increase agriculture-related activities, raise electricity demand in rural area due to increased income for farmers, and together with storms, may affect power transmission and the electricity distribution network (Alam, 2013). In addition, floods frequently hamper transportation networks. To measure the impact of rainfall shocks, we construct a Standardized Precipitation Index (SPI) for each province derived from 'Terrestrial Air Temperature, and Precipitation:

[14]HydroSHEDS DEM was derived from Space Shuttle flight for NASA's Shuttle Radar Topography Mission (SRTM) at three arc-second resolution.

Monthly Climatologies' (version 4.1) by the Daleware University (Matsuura and Willmott, 2009). Positive values of SPI indicate a positive rainfall shock while a negative SPI indicates a negative rainfall shock. Near-zero values of SPI indicate normal rainfall conditions while large values indicate extreme weather conditions.[15]

#### 2.4.2.3 Summary Statistics

Table 2.1 provides a series of summary statistics for our regression sample. Compared with the 2005 sample, the sample in 2015 is characterized by a higher number of smaller firms, domestic private firms, fewer exporters, publicly quoted firms, and those firms that have access to credit. In terms of power provision, firms in the 2015 Survey on average have access to a more reliable power supply regardless of how we measure power outages and the variation across firms is also lower. An average firm in the 2005 Survey experiences 0.6 outages per month, which typical last 2.51 hours while an average firm in the 2015 Survey experiences 0.37 outages per month, which typically last 1.46 hours each. The average outage volume is 4.61 hours/month in the 2005 Survey and 3.12 hours/month in 2015 Survey. This suggests an improvement in the overall reliability of the power system. The share of firms that own a generator is comparable between the two surveys (34% in 2005 and 35% in 2015). In terms of performance, firms in the 2015 Survey have higher average productivity levels, however, because they use fewer inputs they subsequently generate lower revenues.

[**Table 2.1 about here**]

[15] As the measure fits a rainfall series into a gamma series to account for the skewness of rainfall, it has a number of benefits not shared by those used in the literature (Duflo and Pande, 2007; Kaur, 2014; Sarsons, 2015), which construct rainfall shocks from the long-term mean, and for certain degree assume normality of the rainfall series. See Appendix 2.B.3 for more details about the spatial interpolation, and computation methods used in this paper.

### 2.4.3 OLS Estimation

Table 2.2 presents our estimates of the impact of outages on firm revenues. The coefficients on the variable of interest after controlling for firms characteristics, province characteristics, and sector dummies, are negative but insignificant. The results suggest that power outages have no effect on firm performance in both years.

**[Table 2.2 about here]**

Turning to the other controls, in Table 2.3 we present our OLS estimates of the impact of power outages on productivity (Panel A), firms' use of energy inputs (Panel B), and firms' use of other flexible inputs (Panel C). We include the same controls as Table 2.2 including sector dummies but not reported for reasons of space. Panel A shows that for 2004 power outages resulted in a significant reduction in TFPR estimated by the YKL model. More precisely, one percent increase in power outage intensity is associated with a reduction in TFPR by 0.06%, while the equivalent reduction for power outage frequency is 0.15%, everything else equal. The estimates are significant at the 10%, and 1% level, respectively. The coefficients for 2014 are also negative but insignificant. When material inputs are taken into account in the TFPR estimation (YKLM model), the impact of power disruption is insignificant in both years.

Panel B presents the results for the use of a series of different factor inputs. The top panel shows a significant increase in generator use in both years. A 1% increase in the volume of power outages increases the share share of self-generated power by 0.09% in 2004, and 0.05% in 2014. Due to the difference in the availability of energy input variables in the two waves of WBES, we report results for two different dependent variable sets in Panel B: energy cost only for the 2005 Survey, and electricity cost and fuel cost for the 2015 Survey.[16] Our OLS results show no significant change in energy use. Unexpectedly, a 1% increase in power outages is associated with 0.06%-0.11% increase in electricity costs and may reflect the previously discussed issues of endogeneity. Finally, in Panel C we investigate the relationship between power reliability, and non-power flexible factor utilization. Again, in both years power outages are not found to affect the amount of material inputs or the number of workers employed within a firm.

## 2.5 Instrumental Variable Approach

To overcome these challenges to the OLS approach from endogeneity concerns, we employ an instrumental strategy that integrates information about weather, river flow, hydropower generation and the electricity grid. We exploit the fact that Vietnam is highly dependent on hydropower and diverse in topography and weather conditions and hence the weather-induced variations in river flows into large dams may well predict power provision while there is little reason for them to correlate with firm performance via other channels. Before detailing our strategy, we discuss how it is expected to appropriately address the empirical challenges.

The literature suggests three main sources of endogeneity that one may need to consider when examining the link between power outages and firm performance. First, attenuation bias due to measurement error could be serious because we need to rely on self-reported data and hence the degrees of power outages reported could be correlated with unobserved characteristics

[16]The WBES 2005 survey has limited support documentation other than the questionnaire itself which unfortunately does not include a precise explanation of the 'energy cost' variable. Correspondences with World Bank staff suggests that energy cost in 2005 is likely to include both electricity and fuel costs rather than just the cost of electricity alone.

of firms that we were not able to control for. Second, power outages and firm performance could be decided by business environment, and most importantly local economic growth in our context. While this factor benefits firm performance and simultaneously increases resources to upgrade facilities and infrastructures in general, the improvement needs time and is normally lagged behind the demand in developing contexts. Consequently, the places where the economy grows fast tend to experience more overloads (i.e., power supply cannot meet demand spike.) This source of endogeneity also tends to bias the impact of power outages to zero. Finally, firms can choose their initial location to best fit their businesses and in many cases including the consideration of power quality and the location later decides the performance of firms. For example, energy-intensive firms tend to locate where the power supply is more reliable.

As our instrumental strategy exploit an arguably exogenous source of variation (the weather), there is little reason for the IV correlated with firm performance other than through power outages driven by river-flow variation. In other word, there is little chance for our IV to relate to unobserved characteristics of firms or business environment given a rich set of control variables and therefore we are confident that our strategy is good at dealing with the two first sources of endogeneity. Given the cross-sectional nature of our analysis, we need to carefully consider the implication of endogeneity due to firm location as mentioned in Cole *et al.* (2018). We however may argue that our IV strategy is appropriate despite this concern as long as firms do not care about their relative location to hydropower dams used to construct the IV. Different from the case of Sub-African countries investigated in Cole *et al.* (2018), geographical features of Vietnam generate no compelling incentive for firms to locate near hydropower dams. These dams are all situated in mountainous regions, where conditions for doing business are much less preferable and all firms considered in WBES in fact gather in delta regions, which can offer much better facilities, access to markets and human resources. There is also restricted reason for firms to relocate based on their expectation of rainfall variation at surrounding dams given their distance to dams. In addition, dam performance is subject to short-term variations and hence difficult to affect a long-term decision like firm location.

### 2.5.1 River Flow Simulation

At a national scale it is difficult, and prohibitively costly to obtain discharge data for a large number of stations over a long period. Hence, we use the Soil and Water Assessment Tool (SWAT) (Arnold *et al.*, 1998) to simulate river flow. SWAT is one of the most widely used water quality watershed, and river basin–scale models, and is applied extensively to a broad range of hydrologic and/or environmental problems (Gassman *et al.*, 2014, p. 1).[17]

The simulation process follows the approach taken by Nguyen-Tien *et al.* (2018). First, we deploy HydroSHEDS (Hydrological data, and maps based on SHuttle Elevation Derivatives at multiple Scales) (Lehner *et al.*, 2008), and its subset HydroBASINS (Lehner and Grill, 2013) to delineate the watershed.[18] The watershed used in this paper is shown in Figure 2.1 and is a combination of three large basins with a total area of 977,964 km$^2$ as defined by the 'FAO Rivers in

[17]SWAT is a physically based, continuous, semi-distributed model that was initially developed to project the impact of land management practices on water, sediment, and agricultural chemical yields in large complex catchment areas under various soil conditions, land use, and management over a long time period (Neitsch *et al.*, 2009). It is a continuation of thirty years of non-point source modelling by the US Department of Agriculture (USDA), the Agricultural Research Service (ARS), and Texas A&M University. Other federal agencies also contributed to the model, including the US Environmental Protection Agency, the Natural Resources Conservation Service, the National Oceanic, and the Atmospheric Administration, and the Bureau of Indian Affairs.

[18]HydroSHEDS is a derivative of the digital elevation model (DEM) at a three arc-second resolution of the Shuttle Radar Topography Mission (SRTM). The elevation data was void-filled, hydrologically processed, and corrected to produce a consistent, and comprehensive suite of geo-referenced data that enables the analysis of upstream, and downstream connectivity of watersheds. Among the subsets of the HydroSHEDS database, the polygon layers that depict watershed boundaries, and sub-basin delineations at a global scale critical for hydrological analysis are termed HydroBASINS.

South, and East Asia": Red River (165,007 km$^2$), Vietnam Coast (186,187 km$^2$), and a part of Mekong River (similar to Lower Mekong River with an area of 626,771 km$^2$). The watershed was selected to take into account the interconnection of Vietnam's rivers with those in upstream countries. The watershed is divided into 7,887 sub-basins at level 12 of HydroBASINS. ArcSWAT then further divides the watershed into 53,024 terrain units called Hydrologic Response Units (HRU) that are heterogeneous in terms of soil, land cover conditions, and slope thanks to the inputs from the Digital Soil Map of the World (DSMW) (version 3.6) (FAO, 2007), the University of Maryland Department of Geography (UMD) Land Cover classification collection at the 1km pixel resolution (Hansen *et al.*, 1998, 2000), and HydroSHEDS void-filled DEM. Daily weather data for the watershed (the maximum, and minimum temperature, precipitation, wind speed, relative humidity, and solar radiation) were supplied by 2,755 gridded stations from the Climate Forecast System Reanalysis (CFSR) by the US's National Centers for Environmental Prediction (NCEP) (Saha *et al.*, 2010, 2014) to simulate monthly river flow for the whole watershed for the period from January 1995 to July 2014. The simulation period was chosen to best fit the available performance data of hydropower plants, subject to the availability of weather data.

**[Figure 2.1 about here]**

### 2.5.2 Hyropower Generation Model

Our analysis focuses on the river flow into the 40 largest hydropower plants in Vietnam. Our hydropower operation data at the plant level is from Electricity of Vietnam (EVN, 2015*b*) and includes total capacity, and the electricity generation of 40 of the largest hydropower plants in

Vietnam between 1995 and 2014. The combined installed capacity accounts for 75-85% of all hydropower sources which in turn accounts for 35%-53% of energy generation across Vietnam.

**[Figure 2.2 about here]**

We use regression analysis to predict hydropower supply at each of the 40 large hydropower dams in Vietnam between 1995 and mid 2014. This model utilizes installed capacity, a quadratic function of SWAT simulated flow, upstream combined installed capacity, and dam fixed effects as regressors to determine the level of electricity generation. Our estimating equation is given by:

$$Gen_{ist} = \beta_0 + \beta_1 Flow_{ist} + \beta_2 Flow_{ist}^2 + \beta_3 CAP_{ist} + \beta_4 UpCAP_{ist} + \mu_i + \varepsilon_{ist} \tag{2.3}$$

where $i, s, t$ are indices for dam, month, and year, respectively; $Gen$ is average daily generation by month (MWh/day); $Flow$ is the simulated discharge from SWAT model; $CAP$ is the installed capacity of the dam; $UpCAP$ is the combined installed capacity of upstream dams; $\mu_i$ is dam fixed effects, and $\varepsilon_{ist}$ is the idiosyncratic error term. The installed capacity provides us with information on the optimized generation of a given dam at its designed level of discharge, while the function of simulated flow explains the deviation in the generation of electricity due to the deviations in the discharge from the value that the dam was designed for. The inclusion of a squared discharge term reflects differences in turbine efficiency: dams under extreme hydrological conditions (droughts) generate less electricity than predicted given water availability. The upstream installed capacity takes into account the impact of the upstream dams' operation on electricity generation. We include dam fixed effects to take into account other sources of heterogeneity across dams. Table 2.4 presents the results of the model used to generate our IV for the baseline regressions and explains 87.8% of the variation in electricity generation at the dam level.

**[Table 2.4 about here]**

From the results in Table 2.4 we predict the average daily production for each dam by month ($\widehat{Gen}_{ist}$), then calculate the Hydrologically Predicted Plant Factor (HPPF) given by:

$$HPPF_{ist} = \frac{\widehat{Gen}_{ist}\ (MWh/day)}{CAP_{ist}\ (MW).24\ (hours/day)}.100\% \tag{2.4}$$

where $\widehat{Gen}_{ist}$ is the predicted value of dam generation in Equation 2.3, which excludes the error term $\varepsilon_{ist}$ that could be correlated with power demand fluctuation. The $HPPF$ is the ratio between predicted generation, and the generation under full utilization at the designed discharge. $HPPF$ of a dam at a given time point is mainly determined by the hydrological conditions at that dam (water availability, and flow extreme degree); which in turn are driven by weather conditions, and not affected by human activities or firm performance.

We calculate the HPPF for each year as the average of HPPF for each month in that year:

$$HPPF_{it} = \frac{\sum_{s=1}^{T} HPPF_{ist}}{T} \tag{2.5}$$

Where $T$ is the number of months in a year: $T = 12$ for $t = 2004$, and $T = 7$ for $t = 2014$, as we were not able to simulate river-flow series for the last 5 months of 2014 due to the unavailability of weather data. [19] It should be noted that for each survey, we used a different number of hydropower plants to calculate $HPPF$, taking into account the dynamics of dam

[19]The incompleteness of the series however does not affect the IV for 2014 as the first 7 months already cover the entire dry season when the variation in river flows to hydropower dams is most likely to affect power reliability. As the last 5 months are within the rainy season, outages due to hydropower are less of a concern.

hydropower construction: 11 for the 2005 Survey, and 40 for the 2015 Survey (for details see Table 2.5).

**[Table 2.5 about here]**

### 2.5.3 Linking Provinces and Hydropower Plants

After estimating hydropower plant factors based on weather shocks, we need to link the performance of power utility companies with the power provided to firms. One solution is to define a cutoff radius (100km, 200km or 400km) to determine the hydopower plant that supplies a certain province before constructing an instrumental variable (Cole *et al.*, 2018). However, this approach is not appropriate for a country like Vietnam that has a single grid system that connects all provinces and power sources. More specifically, since 1994, Vietnam has constructed, and operates a 500kV North - South line that has enabled the interconnection and exchange of electricity across regions. For example, a power shortage in a large industrial centre in the South could be filled by the transfer of a surplus of supply of a power plant located in the North. Hence, in our single grid context, it is important to incorporate the performance of all hydropower plants for each province centre. We consider two factors: the size, and the distance of the utility to our sample of firms.

Distance plays an important role in energy transmission, especially in the single-grid system like the case we deal with in this study. Although electricity is a special goods, which can be consumed almost immediately after generation at any point on the grid Cole *et al.* (2018), underdeveloped transmission and distribution system like the case of Vietnam means that a long distance of power transmission is associated with large variable technical losses (Hussain *et al.*, 2018). When a large hydropower plant needs to decrease its generation due to a shortage of water, it is more efficient for the overall system to reduce supply to economic centres within the proximity of the plant first. Otherwise, extra electricity from distant sources is required to be transmitted to fill in the local power demand gap at the cost of power shortages at other economic centres plus large technical losses due to long-distance transmission.

The size of a utility can be proxied by its installed capacity. However, we need to construct a measure of distance. Figure 2.3 shows the provinces in the WBES, the hydropower plants used in this study and the electric grid network that connects them.

**[Figure 2.3 about here]**

#### 2.5.3.1 Distance to Hydropower Plants

A simple solution is to estimate the geodesic distance, the minimum length of a curve that links a province centroid to a hydropower dam along the surface of the earth.[20] However, Geodesic distance is a fairly coarse measure as it does not take into account the distribution system (grid) of the country. Our solution is to construct a second distance measure through the electricity transmission network based on the grid GIS dataset by WB (2017) (see Appendix 2.B.4 for details).

[20] More specifically, we compute this distance by the *geodist* package by Picard (2017), which uses the coordinates in the WGS 1984 datum, and the equations in Vincenty (1975).

#### 2.5.3.2 Instrumental Variable Computation

We incorporate the $HPPF$ from listed hydropower sources to compute an instrumental variable that we call the Hydropower Availability Index ($HAI$) for each province and reflects the power supply availability in that province given by:

$$HAI_{jt}(\rho) = \frac{\sum_{i=1}^{N} HPPF_{it}.w_{ijt}}{\sum_{i=1}^{N} w_{ijt}}, \text{ where } w_{ijt} = \frac{CAP_{it}}{d_{ij}^{\rho}} \tag{2.6}$$

Accordingly, Hydropower Availability Index ($HAI$) of province $j$ in year $t$ is the weighted average of $HPPF$ of all ($N$) hydropower plants (indexed by $i$) within our sample in that year. The weight $w_{ijt}$ is proportionate to the installed capacity of plant $i$ but inversely related to the distance raised to power $\rho$ between plant $i$, and province $j$ ($d_{ijt}^{\rho}$).

### 2.5.4 Distance Penalty Parameter Selection

One important aspect in the calculation of our IV is that is may be sensitive to the selection of the distance penalty parameter ($\rho$). Hence, we need to make a decision on the value of $\rho$ for each survey. As can be seen from Table 2.6, increasing $\rho$ tends to give us a lower minimum and higher maximum values and a larger variation (measured by the standard error). A higher penalty for distance means it is harder to smooth power production across the country, and a more 'localised' measure of our hydrological predictor of power shortages and can take on more extreme values.

[**Table 2.6 about here**]

It is useful to consider each cross section in turn. A firm located in a province with higher *HAI* is less likely to be constrained by poor power supply conditions everything else equal. However, because in a given year, there is only one transmission and distribution system, there should be only one value of $\rho$ that is the most suitable to describe the system at that time. As we have limited information on the power transmission and distribution system we rely on our WBES sample to choose a suitable value of $\rho$ for each survey.

For our IV to be a valid instrument it must be correlated with our outage measures (the relevance condition) but should not drive firm performance via any channel other than through the deficiencies in the power supply (the exogeneity condition). As we intend to use a single hydro-IV for our endogenous variable (power outages), it is not possible to formally test the exogeneity of our IV. However, as our IV is generated from an arguably exogenous source of variation (the weather), it is difficult to imagine any mechanism through which the hydro-IV could influence firm performance other than through power outage once factors that may give cause for concern in the literature such as cooling degree, and rainfall shocks (Allcott *et al.*, 2016; Alam, 2013) are controlled for. One may concern that our IV (HAI) is computed from a non-linear function of distance and therefore could be just a proxy for the remoteness, for example if economically or politically important provinces are by chance relatively close to hydropower dams in shortage of water. The exogeneity of our IV however remains given such a valid concern as we already control for industrial production share, which captures the importance of the provinces in the national industry. Our IV generation process ensures that our hydro instruments are not dependent on weather local to the firm but the weather conditions upstream from the dams (and in some cases even beyond Vietnam's borders) that generate electricity supplied to the local region where the firm is located. For this reason, we argue that we have a good instrument.

We now discuss why we believe that our IV is relevant. Besides the usual *t-tests*, which are derived from the heteroscedasticity-robust standard errors clustered at the province level, we adopt an underidentification test to check whether the 'reduced form' equation is identified, namely the Sanderson-Windmeijer (SW) first-stage $\chi^2$ test (Sanderson and Windmeijer, 2016).[21] We also consider the problem of weak instruments, which may bias the 2SLS estimates, and make the size of associated tests less reliable (Stock and Yogo, 2005). The widely-used rule of thumb by Staiger and Stock (1997) suggests that an IV should not be used if the first stage F-statistic is less than 10. In our case, to report a first stage F-statistic we rely on the Kleibergen-Paap rank Wald F statistic, which is generalised for the non-*i.i.d* errors (Kleibergen and Paap, 2006; Kleibergen and Schaffer, 2007). A remedy for a weak IV (if any) is to use a test that is robust to weak instruments for the significance of the potentially endogenous variable. Hence, we use the Anderson-Rubin (AR) test (Anderson and Rubin, 1949) where the null hypothesis is that the coefficients on the endogenous variable in the structural equation (*power outage*) are not statistically different from zero, and the overidentifying restriction is valid.

Our approach is to run the first stage with the same set of control variables as the OLS estimations, using $HAI(\rho)$ with varying values of $\rho$ as an instrument for the measurement of outages. Hence, to be considered as a possible instrument the variable must be relevant (i.e., correlated with the outage measurements conditional on the control variables) and the correlations should be negative (i.e., less hydro-availability is associated with a greater risk of a power supply shortage). Among the qualified candidates for the choice of IV, for a given set of control

[21]The SW test builds on the procedure by Angrist and Pischke (2008)[p217-218], and implemented using the *ivreg2* command (Baum *et al.*, 2010).

variables, we favour those that return the highest values in the first stage Kleibergen-Paap rank Wald F-statistic. For the 'calibration' process we use the values of $\rho$ from 1 to 10 with one unit intervals with revenues (in logs) as the dependent variable (of the second stage).

We use Figure 2.4 to illustrate the performance of the first stage analysis for different choices of $HAI(\rho)$. In all of the graphs the coefficients of $HAI(\rho)$ in the first stage regression, represented by the red lines, lie below the blue horizontal lines (constant value at 0) and the province-clustered robust confidence interval bands (grey areas) do not touch the blue lines in any of the graphs presented. These indicate that the IVs that we generate in the first stage are within the chosen range of $\rho$, are negative and relevant. This gives us a certain flexibility when it comes to the selection of IVs for the main regressions results.

[**Figure 2.4 about here**]

For the 2005 Survey we choose $\rho = 1$ for the baseline regressions where the IV is at its most powerful (highest blue bars) regardless of which measure of power outage is used. For the 2015 Survey the IV is strongest when $\rho = 9$ for outage frequency and $\rho = 10$ for outage intensity and volume. As a result, for the firms in the 2015 Survey, we choose $\rho = 10$ to generate the IV for our baseline 2SLS regressions. The first stage has allowed us to decide on an optimal value for the distance penalty parameter for the models that use different measures of outages and gives us confidence in the selection process given our prior belief that in each year there should be only one value of $\rho$ that best describes the current system of power transmission and distribution. One possible explanation for the higher value of $\rho$ in 2015 is that more hydropower plants were used in the constructions of the IVs (40 vs 11). When the network of power sources became more intensive, the impact of each plant tends to be more localised (i.e., a local utility is more important to local supply) and hence one might expect a higher distance penalty parameter ($\rho$).

## 2.6 Results

### 2.6.1 Baseline First Stage Results

Table 2.7 presents the results of our baseline first stage regressions (where revenue is the dependent variable in the second stage) using our chosen IVs for each survey. The IVs are negatively correlated with our outage measures and the correlations are significant at the 1% level. The exception is the correlation between $HAI(1)$ and outage frequency in the 2005 Survey (Column 1), which is significant only at the 5% level. The first stage (Kleibergen-Paap rk Wald) F-statistic for this column is lower than the rule of thumb (6.08) while those of the five others exceed 10, ranging between 13.29 (Column 4), and 20.12 (Column 2). Hence, our IVs can be considered reasonably powerful. Everything else equal, if the (weighted) hydropower sources that supply a particular firm experience more advantageous hydrological conditions, the firm is less likely to face power constraints across all three measures. Our results for the 2005 Survey show that a one percent increase in $HAI(1)$ corresponds to a 4.34% reduction in outage frequency, a 9.39% decrease in outage intensity, and a 11.65% decrease in outage volume. For the 2015 Survey we find that a one percent increase in $HAI(10)$ corresponds to a 0.71% decrease in outage frequency, a 1.56% decrease in outage intensity, and a 1.76% decrease in outage volume. Under-identification is rejected at the 1% level for each regressions according to the SW $\chi^2$ test, with the exception of Column 1, which is rejected at the 5% level.

[**Table 2.7 about here**]

Table 2.8 provides the first stage results for our other second stage dependent variables (TFPR, and our energy input factors). Due to missing values for a number of these dependent variables, the sample sizes are smaller than those for total revenues. In general, the first stage appears to be consistent across the different samples: The IV coefficients are negative and of a similar magnitude to those shown in Table 2.7 and are generally significant at the 1% level with some only at the 5% level. The exceptions are the estimates for Frequency, and when the second stage dependent variable is a measure of TFPR in the 2015 Survey. However, the under-identification problem of these first stage regressions are rejected at the 10% level implying the IVs are still valid. For the other first stage results, IV irrelevance is rejected at least at the 5%, and for the majority it is rejected at the 1% level. [**Table 2.8 about here**]

### 2.6.2 Second Stage Results

#### 2.6.2.1 Revenues

Table 2.9 provides a comparison of the impact of outages on revenues. In both years, the 2SLS coefficients are negative, and larger than those of the OLS estimates. The smaller coefficients in the OLS results are in line with the hypothesized attenuation biases caused by measurement error, and biases caused by pro-business environment factors and match what was found for India (Allcott *et al.*, 2016).[22] Our findings for 2004 show that, on average, a 1% increase in power outage frequency, intensity, and volume is associated with a loss of 0.74%, 0.34%, and

[22] Omitted environmental factors that support business may increase power demand and put further stress on power supplies, causing more power disruption. This kind of bias pushes the negative impact of power deficiency toward zero.

0.27% in revenue. The coefficients for revenue losses are much larger in 2014, at 1.81%, 0.82%, and 0.73%, respectively.[23] In comparison, the marginal impact of power outages (measured in Volume) on revenue for the case of India is -1.091 (Allcott *et al.*, 2016) and -1.08 for Sub Saharan (Cole *et al.*, 2018). Our significant estimate at -0.73 (for Survey 2015) is slightly smaller, probably because power outages in Vietnam are a less severe issue. The coefficients for the 2005 Survey, however, remain statistically indistinguishable from zero, confirmed by the results of a weak-instrument test. In contrast, the coefficients for the 2015 Survey are significant at the 1% level for all three outage measures. The insignificance of an outage impact is also rejected by the weak-instrument test at the 5% level. Overall, the 2SLS estimates support the view of outages in 2004 had very little impact on firm revenues but in contrast to the OLS results they do provide strong evidence that power unreliability in 2014 had a significant impact.

**[Table 2.9 about here]**

#### 2.6.2.2 TFPR

Panel A of Table 2.10 shows the 2SLS estimates for the impact of power outages on productivity. Again, the 2SLS estimated coefficients are negative and their magnitudes are greater than those estimated by OLS. In line with the testable hypotheses, the size of the productivity losses are smaller than the revenue losses. In 2004, a 1% increase in the power outages decreases the efficiency of machinery, and labor usage by 0.25 - 0.77%, and the efficiency of machinery, labor, and material input usage by 0.13- 0.38%. For 2014 the productivity losses for the same two groups range from 0.55-1.36%, and 0.53-1.30%, respectively. The significance level of these

[23] Based on the summary statistics, a 1% increase in power outage volume equates to 2.8 minutes/month in the 2005 Survey 2005 and 1.9 minutes/month in the 2015 Survey.

coefficients varies. The loss of TFPR measured by YKLM in the 2005 Survey is significant at the 10% level. The loss of TFPR measured by the YKL model in the 2015 Survey is significant at the 1% level. The loss of TFPR measured by the YKLM model in Survey 2015 is insignificant according to the t-test but significant at the 5% level according to the weak-instrument test (AR $\chi^2$).

[**Table 2.10 about here**]

#### 2.6.2.3 Energy Inputs

Panel B of Table 2.10 shows how power deficiency affects a firm's decision on the level of energy to use in the production process. A common adaptation that firms appear to make and that we find evidence for in both years is to use self-generated electricity with the coefficients being significant at at least the 5% level. An increase in the degree of power unreliability explains 0.35%-1.02%, and 0.31%-0.76% of the increase in the share of self-generated electricity in the 2005 and 2015 Surveys, respectively with the magnitude depending on the measure of outages. Of the three measures, firms are more sensitive to the frequency rather than the intensity or volume of outages.

Overall, the higher the level of unreliability in the power supply, the less energy firms use. For the 2005 Survey the magnitude of energy reduction ranges from 0.76-2.03, and is significant at the 5% level (t-test) and the 1% level (AR $\chi^2$ test). The same significance levels are found for the use of electricity in the 2015 Survey with the size of the coefficient ranging between -1.03, and -2.46. The impacts of outages on fuel use in 2015 is found to be negative but not statistically different from zero.

#### 2.6.2.4 Other Inputs

Panel C of Table 2.10 shows the impact on other flexible inputs (material inputs and labor). For both inputs, there is no impact on firms in the 2005 Survey. Those in the 2015 Survey are only significant at the 10% level according to the AR $\chi^2$ test. Hence, in 2014 a one percent increase in power outages is estimated to decrease the use of material inputs, and labor by 0.62-1.39%, and 0.64-1.53%, respectively. The lack of strong results may suggest that firms are not able to substitute factor inputs that easily in the face of power outages.

### 2.6.3 Distance Penalty Parameter Uncertainty Analysis

As part of our sensitivity analysis we investigate whether our 2SLS results are sensitive to the selection of the distance penalty parameter ($\rho$). Figure 2.5 illustrates how the estimates for the responses of revenue to power unreliability change across different values of $\rho$. In both years, the 2SLS estimates (red dots) are negative, and considerably below the OLS estimates no matter which $\rho$ is chosen to generate the IV. The magnitude of the 2SLS coefficients for the 2005 Survey are largest for $\rho = 2$, and gradually decreases as $\rho$ becomes larger. However, the change is negligible in comparison with the standard error of our baseline estimates. As the 95% confidence intervals (grey bands) always cross the green line (zero coefficient) we can conclude that the impact of power outages on revenues in 2004 is insignificant regardless of the value of $\rho$.

[**Figure 2.5 about here**]

However, when we turn to the 2015 Survey we find our results are sensitive to the choice of

$\rho$. From the baseline values, the coefficients increase when the we put a lower penalty ($\rho$) on distance (the size of hydropower plants is more important), and exceeds one deviation from the baseline values when $\rho$ reaches 1. This implies the role of distance causes a range of coefficient uncertainty. Nevertheless, regardless of the value of $\rho$, the coefficients for the 2015 Survey are always negative and significant (at the 5% level or better), and their magnitudes are always larger than those for the 2005 Survey. In Appendix 2.C we provide additional robustness checks to show that our findings are robust to the use of alternative IVs or when regressions are run on subsets of the data.

### 2.6.4 Differences across Years

Our robustness checks reinforce our main results power unreliability was more harmful (both in terms of size and significance) for firm performance in the 2015 Survey than the 2005 Survey. In this subsection we investigate the mechanisms that may be driving this difference. One possible explanation is that the extent to which firms require electricity to operate has intensified. If electricity is mainly used for general purposes, such as lighting, or makes only a minimal contribution to the value-added processes, there is no reason to expect a significant impact of a power outage on firm performance. However, if firms have become more technologically advanced and now operate complex production processes then it is easy to imagine how power outages could become more costly.

To investigate whether the electricity intensity hypothesis holds, we pool all manufacturing firms (that report a value of machine use) and test whether there were changes in factor intensities across the two surveys. We employ a median regressor to estimate the three log-linear versions of the Cobb-Douglas function: YKL, YKLM, and YKLMN, where the YKLMN is an extension of the YKLM, adding energy (N) to the production function. We assume that the energy cost reported in the 2005 Survey is the sum of electricity costs and fuel costs. All regressions include the factor costs of production (in log form), their interaction terms with an indicator for year 2015, and a year dummy. For robust checks, we sequentially include province and sector dummies. The results are presented in Table 2.11.

[**Table 2.11 about here**]

Of primary interest are interactions terms that indicate whether factor intensities change across the two surveys. All nine regressions confirm that there was a significant rise in capital intensity, and the final three columns show that there has also been a significant increase in energy intensity. The magnitude of the shift is relatively large. The results in the final column show that in the 2005 Survey, the intensity of capital is just 2.9% whereas it quadruples to 12.4% in the 2015 Survey. Over the same period the average energy intensity almost doubles from 5.6% to 10.3%. In contrast, material input intensity significantly decreases by 13%. Labour intensity also falls, however the significance of the reduction is not robust, especially when taking material inputs and energy into account.

Assuming the firms in the WBES are representative our results suggest that over the period 2004 to 2014 there was substantial development in the Vietnam manufacturing sector. Firms engaged in more comprehensive, and complicated manufacturing processes that use fewer intermediate material inputs, generate more value from existing capital and energy inputs through the more intensive use of machinery and hence being less reliant on simple product assembly. It is also likely, although we cannot test it directly, that firms also became more electricity intensive and explains Vietnam's increasing sensitivity to changes in the quality of electricity provision. These findings are in line with the policies of industrialisation and modernisation that Vietnam has been keen on pursuing and the observation that Vietnam's economic complexity in the global ranking was improved from 85 in 2004 to 54 in 2014 (Simoes and Hidalgo, 2011).

## 2.7 Conclusions

In this study the impact of power outages on firm performance by introducing an innovative instrumental variable strategy in he context of a small rapidly growing economy. We contribute to the hydro-IV literature by offering a solution for a single-grid country. More specifically we propose a framework that integrates a rainfall-runoff model, a hydropower generation model, and an interpolation technique using grid-based distances to generate an IV that is relevant and powerful. We apply our framework to firm-level data from two waves of the WBES spanning ten years.

Our results suggest that power quality matters for fast growing economies like Vietnam. Firms that face frequent or long lasting power disruptions tend to generate less revenue than their counterparts. We also find that productivity is lower and they use less flexible inputs, such as material inputs and labor.Power outages also induce firms to use generators to supply more of their electricity. Of the different types of outage, increased frequency is more damaging than intensity. Comparing the impact of power outages in 2004 and 2014, we find that firm performance appears to be less responsive to the low quality of power supply and not surprisingly became more sensitive as firms became more dependent on electricity. This finding supports the progressive approach in power development policy making. Our results that show an increase in production complexity over time also helps us to understand the differences in the empirical results compared to previous studies, where the reduction in revenues due to power outages are found to be significant in some (Allcott *et al.*, 2016) but insignificant in others (Mensah, 2016).

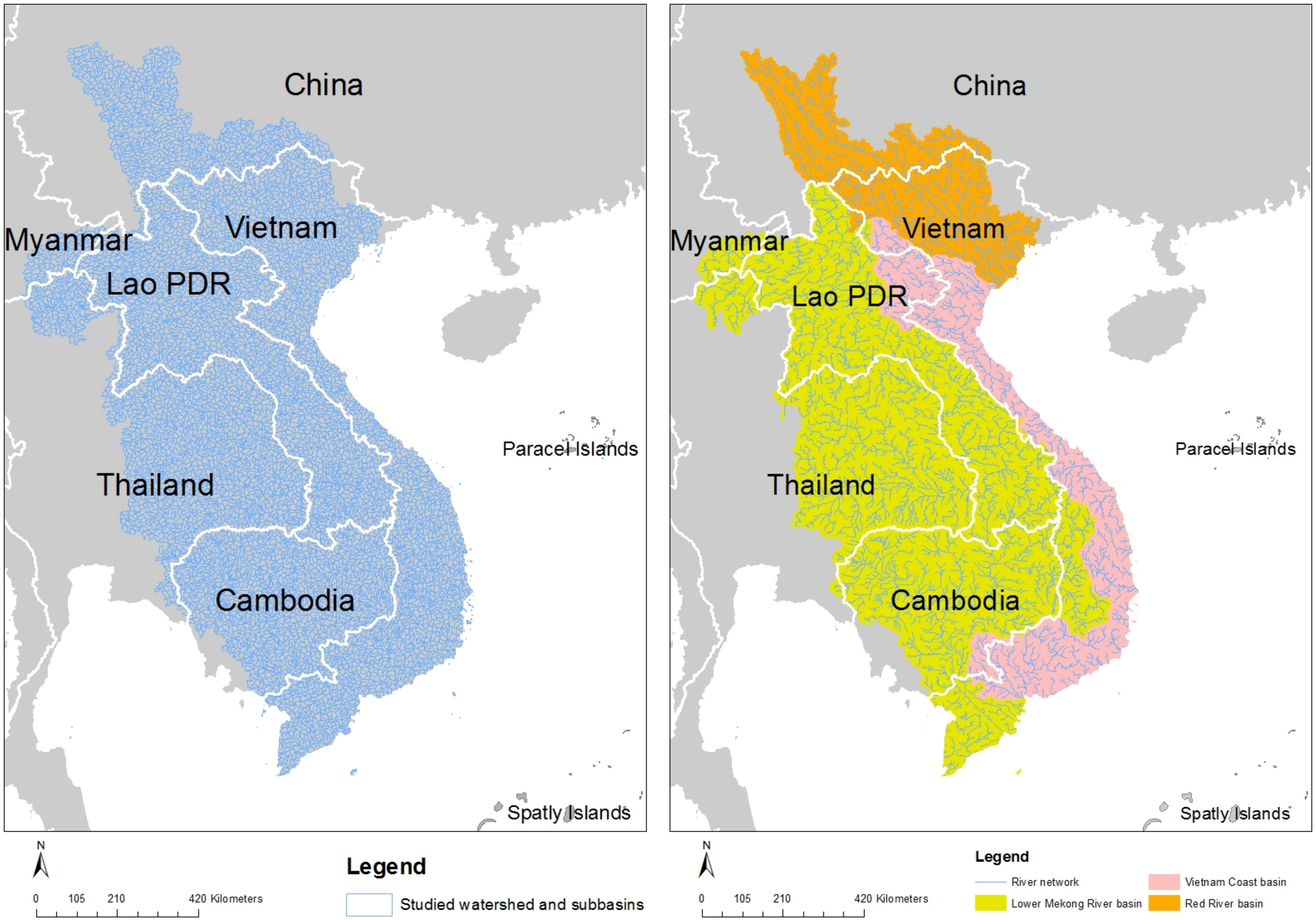
In terms of policy prescriptions, our results show that an improvement in power reliability could substantially enhance economic growth. According to our 2SLS estimates, in 2014 a small reduction in power disruption by 22.8 minutes per year would have increased revenues by 0.73%. Given that total revenues of registered firms in 2014 was 13,516 trillion dong (639 billion USD), and assuming that firms in WBES are representative, such an improvement in power quality could have added 4.66 billion USD to the performance of Vietnam's firms.[24]

The greater vulnerability of firms to power disruption in recent years reflects the changes that Vietnam has made in moving up the global value chain, where simple product assembly and processing has been replaced by more comprehensive manufacturing sector that uses machinery, and energy more intensively. Other solutions to reduce firms' sensitivity to power outages include the promotion of power-saving technologies and to price electricity at full price to encourage greater inward investment in the sector. The potential for the latter is significant as it has been identified that by 2030 Vietnam potentially could save 17% electricity if appropriate energy efficiency polices were introduced (Danish Energy Agency, 2017).

[24]Total revenues of registered firms is from Vietnam General Statistics Office (GSO). The average official exchange rate for 2014 (1USD= 21,148 VND) is from International Monetary Fund, International Financial Statistics.

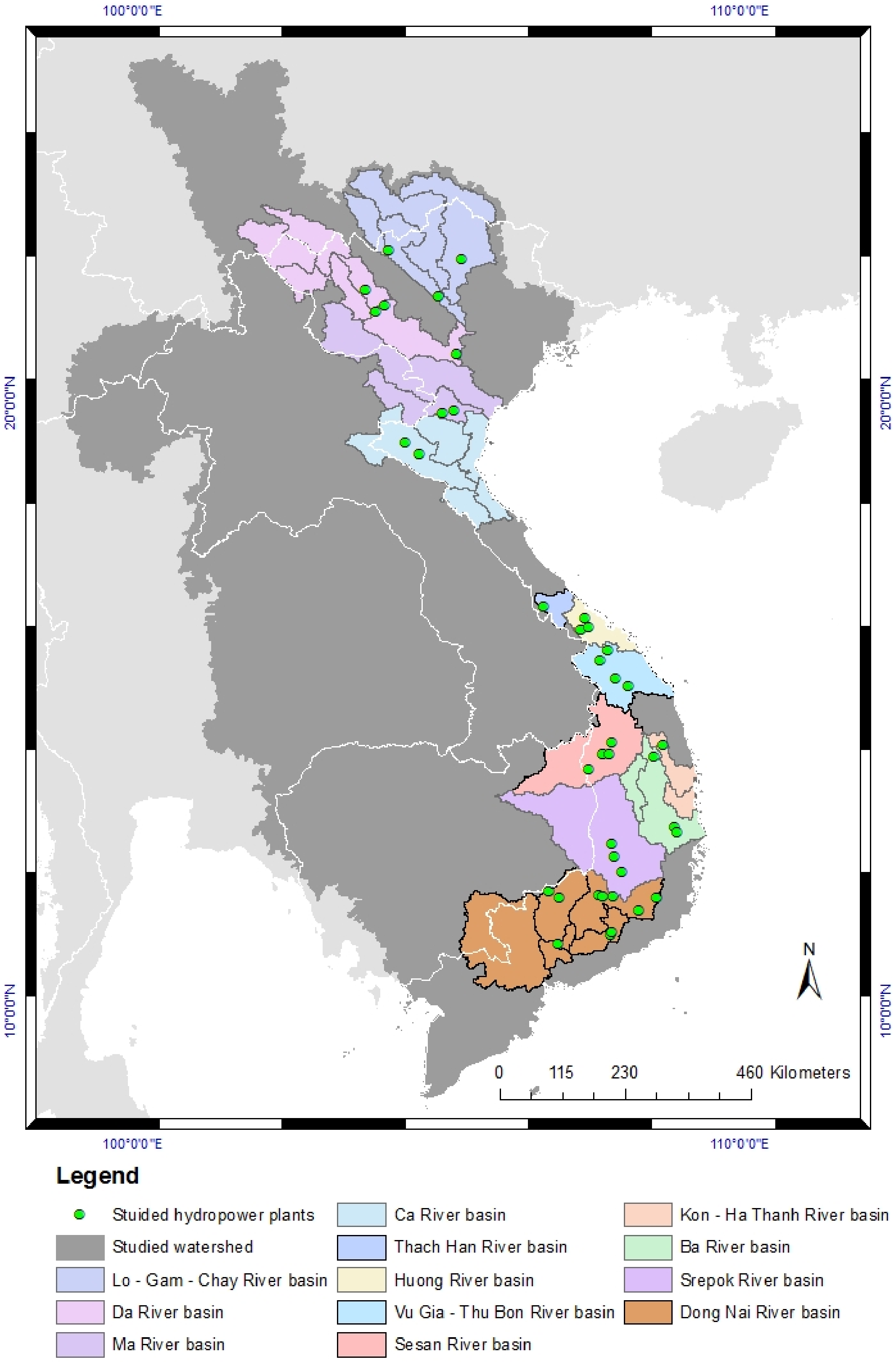
**Figure**

**Figure 2.1: Watershed delineation**



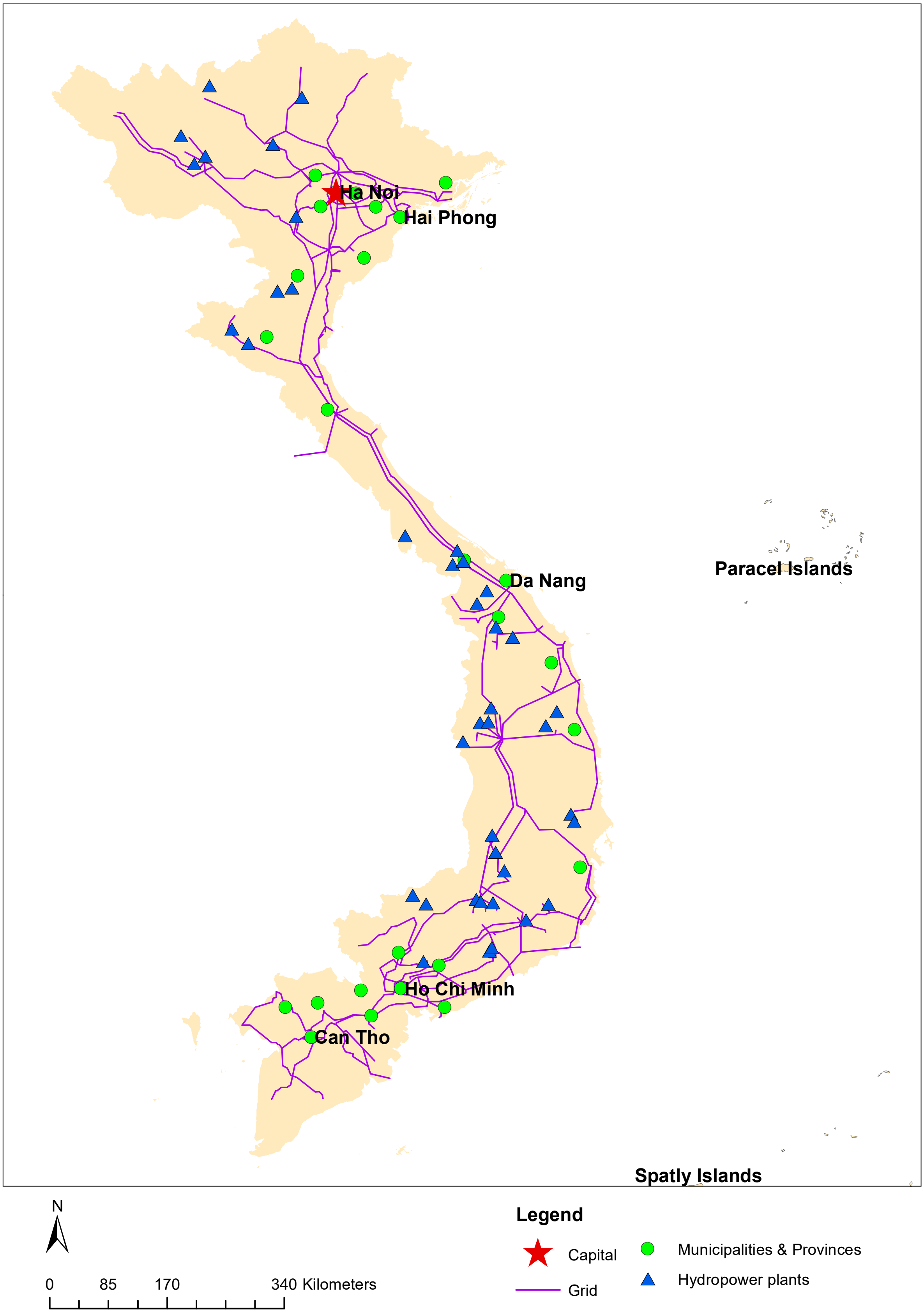

Source: Authors compiled from HydroSHEDS and HydroBASINS. Notes: The solution of HydroSHEDS void-filled DEM is 3 arc-seconds. The resolution of HydroBASINS river network is 15 arc-seconds. The watershed is shared by Vietnam, China, Myanmar, Lao PDR, Thailand and Cambodia. The area within Vietnam accounts for 32.22% the total area of the watershed and covers 96.15% (315,122 km$^2$/327,727 km$^2$) of Vietnam's mainland area. The remainder belongs to the Bang Giang – Ky Cung river basin, which makes no meaningful contribution to Vietnam's overall hydropower production.

**Figure 2.2: Basins and hydropower plants**




Source: Basins are derived from "FAO Rivers in South and East Asia" and MONRE (2012).

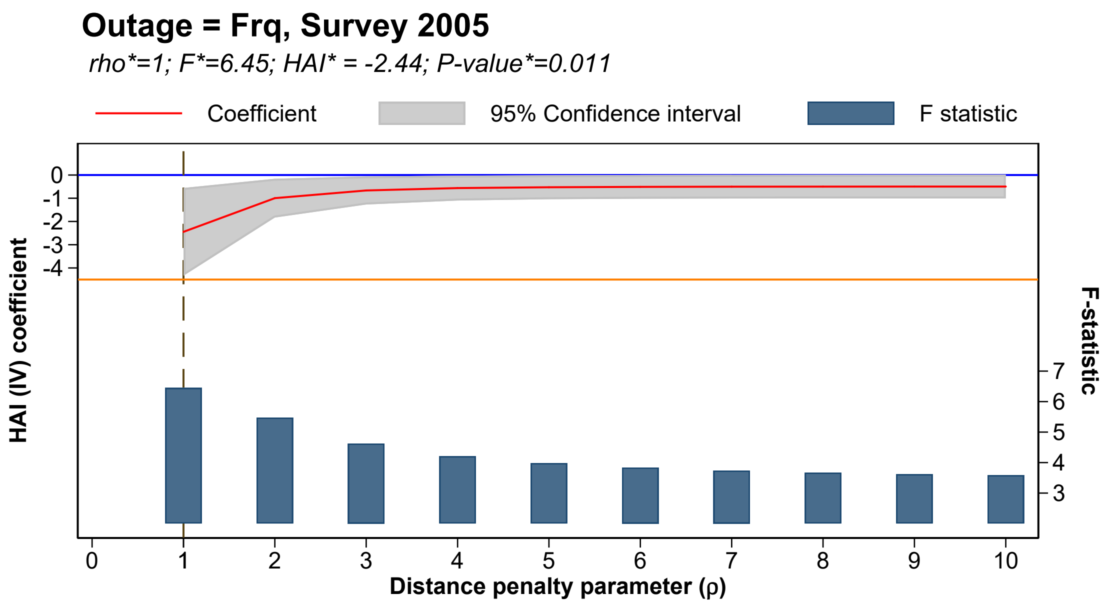
**Figure 2.3: Provinces, hydropower plants and electric grids in Vietnam**

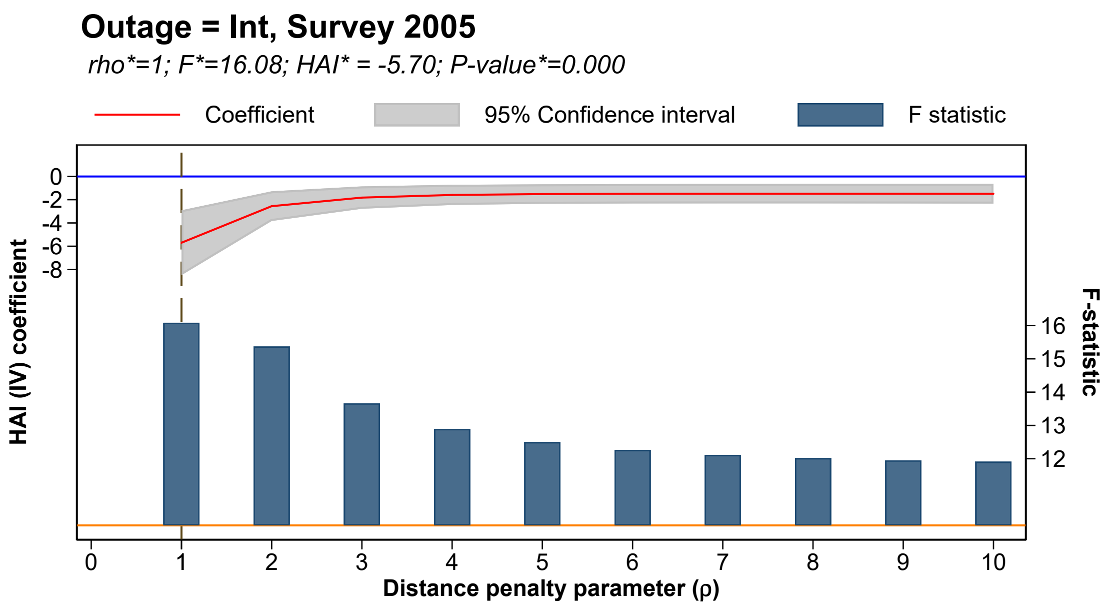


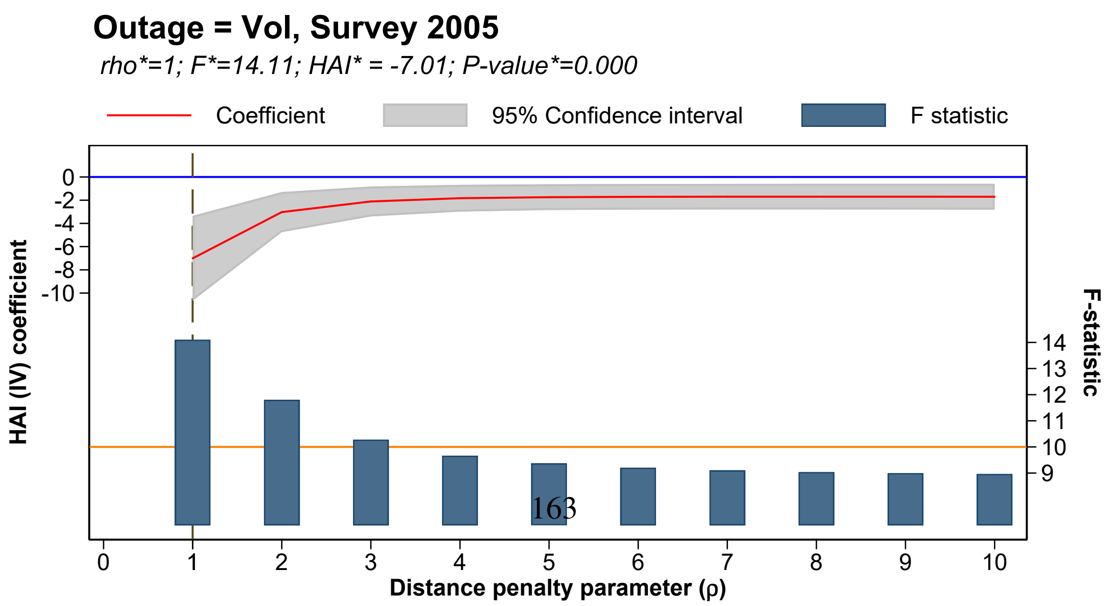

*Note:* The administrative map is derived from GAUL dataset (FAO, 2015). The electric line network is from (WB, 2017).

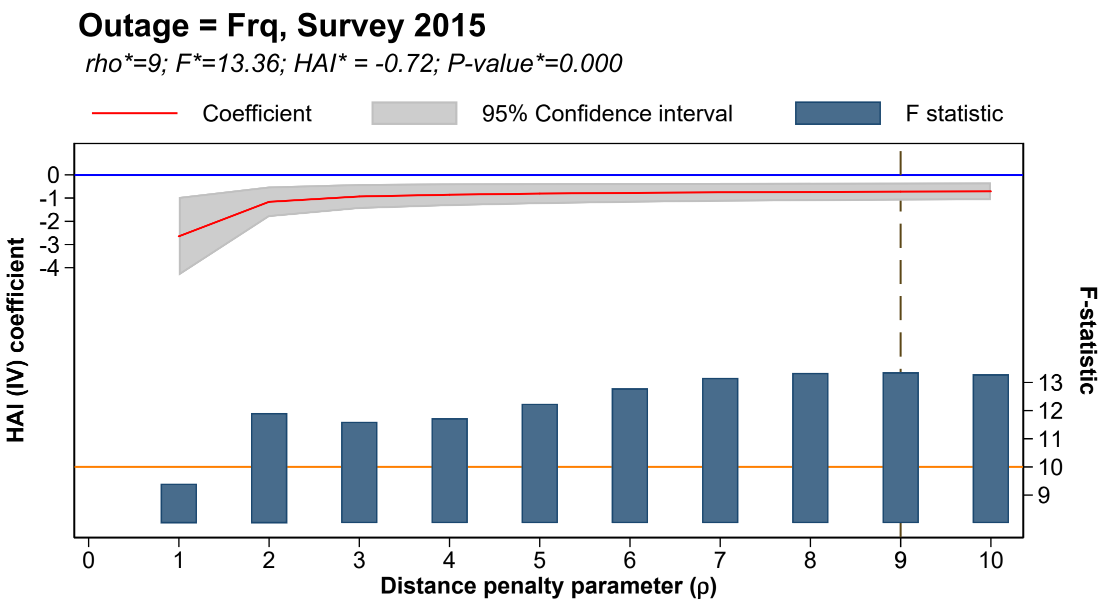
**Figure 2.4: First stage performance using *HAI*($\rho$) as the IV and varying the distance penalty parameter ($\rho$)**

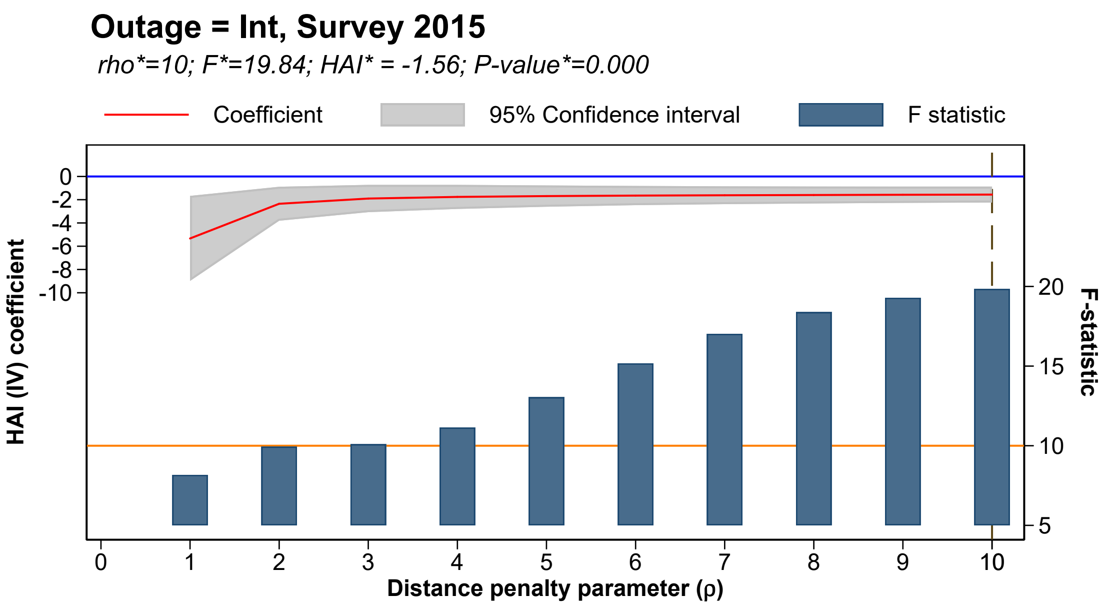
*Note:* The graphs in the subsequent pages illustrate the performance of our first stage regressions. The dependent variable in the second stage is the log of revenue. The endogenous explanatory variable in the second stage (the dependent variable in the first stage) is a measure of power outages. The excluded instrumental variable is $HAI(\rho)$ defined in Section 2.5 and determined by a series of distance penalty parameters ($\rho$) from 1 to 10 with an interval of 1. The control variables are as those in Table 2.2 (including sector dummies).
The title of each graph indicates the measure of power outages, which could be *Frq* - Frequency (average number of outage per month); *Int* - Intensity (average duration (hour) per outage); and *Vol* - Volume (average outage hour per month = $Frq \times Int$) and the WBES data used.
The subtitle of each graph reports the optimal value of $\rho$; defined as that which produces the highest F-statistic in the first stage and the value of the F-statistic, the estimate of the instrument coefficient $HAI(\rho)$ in the first stage and its p-value corresponding to the optimal $\rho$.
Each graph draws the estimate of coefficient of *HAI* (line, left y-axis), its 95% confidence interval (area, left y-axis) and the F-statistic (bar, right y-axis) of the first stage regression for each value of $\rho$ within the stated range.
The vertically dashed line is drawn at the optimal value of $\rho$. The horizontal line at 0 (blue, left y-axis) is drawn with reference to the confidence intervals to identify the significance of the coefficients. The horizontal line at 10 (orange, right y-axis) is sketched with reference to the F-statistic to identify the "weak" instrument issue, based on the rough rule of thumb (F-statistic <10).
F statistic reported is for the heteroskedasticity Kleibergen-Paap weak instrument test.


Outage = Frq, Survey 2005
rho*=1; F*=6.45; HAI* = -2.44; P-value*=0.011
Coefficient
95% Confidence interval
F statistic
HAI (IV) coefficient
F-statistic
Distance penalty parameter (ρ)


Outage = Int, Survey 2005
rho*=1; F*=16.08; HAI* = -5.70; P-value*=0.000
Coefficient
95% Confidence interval
F statistic
HAI (IV) coefficient
F-statistic
Distance penalty parameter (ρ)


Outage = Vol, Survey 2005
rho*=1; F*=14.11; HAI* = -7.01; P-value*=0.000
Coefficient
95% Confidence interval
F statistic
HAI (IV) coefficient
F-statistic
Distance penalty parameter (ρ)


Outage = Frq, Survey 2015
rho*=9; F*=13.36; HAI* = -0.72; P-value*=0.000
Coefficient
95% Confidence interval
F statistic
HAI (IV) coefficient
F-statistic
Distance penalty parameter (ρ)


Outage = Int, Survey 2015
rho*=10; F*=19.84; HAI* = -1.56; P-value*=0.000
Coefficient
95% Confidence interval
F statistic
HAI (IV) coefficient
F-statistic
Distance penalty parameter (ρ)

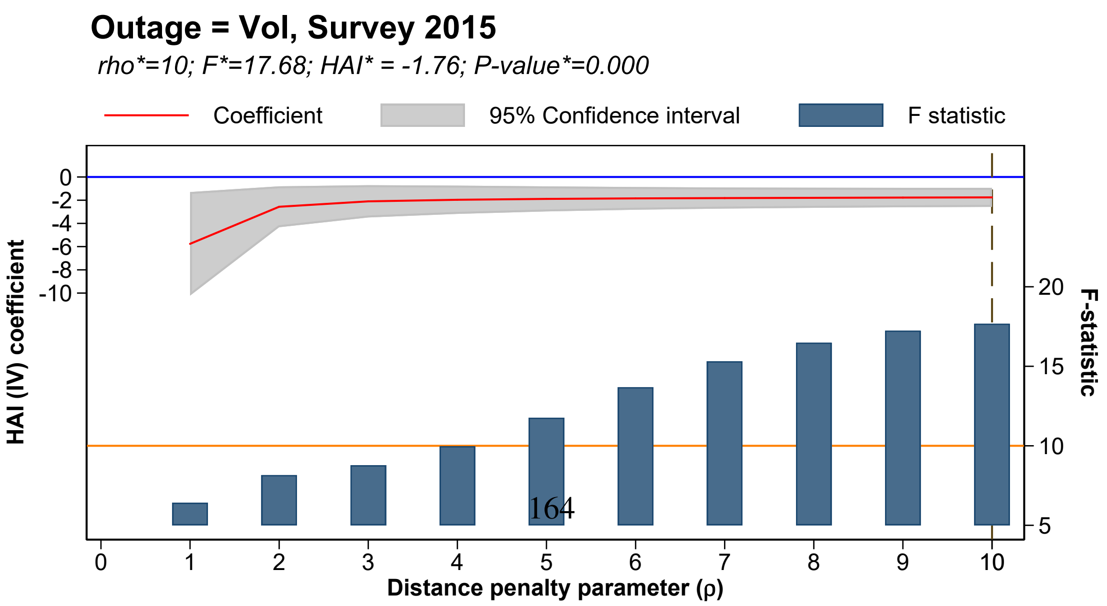
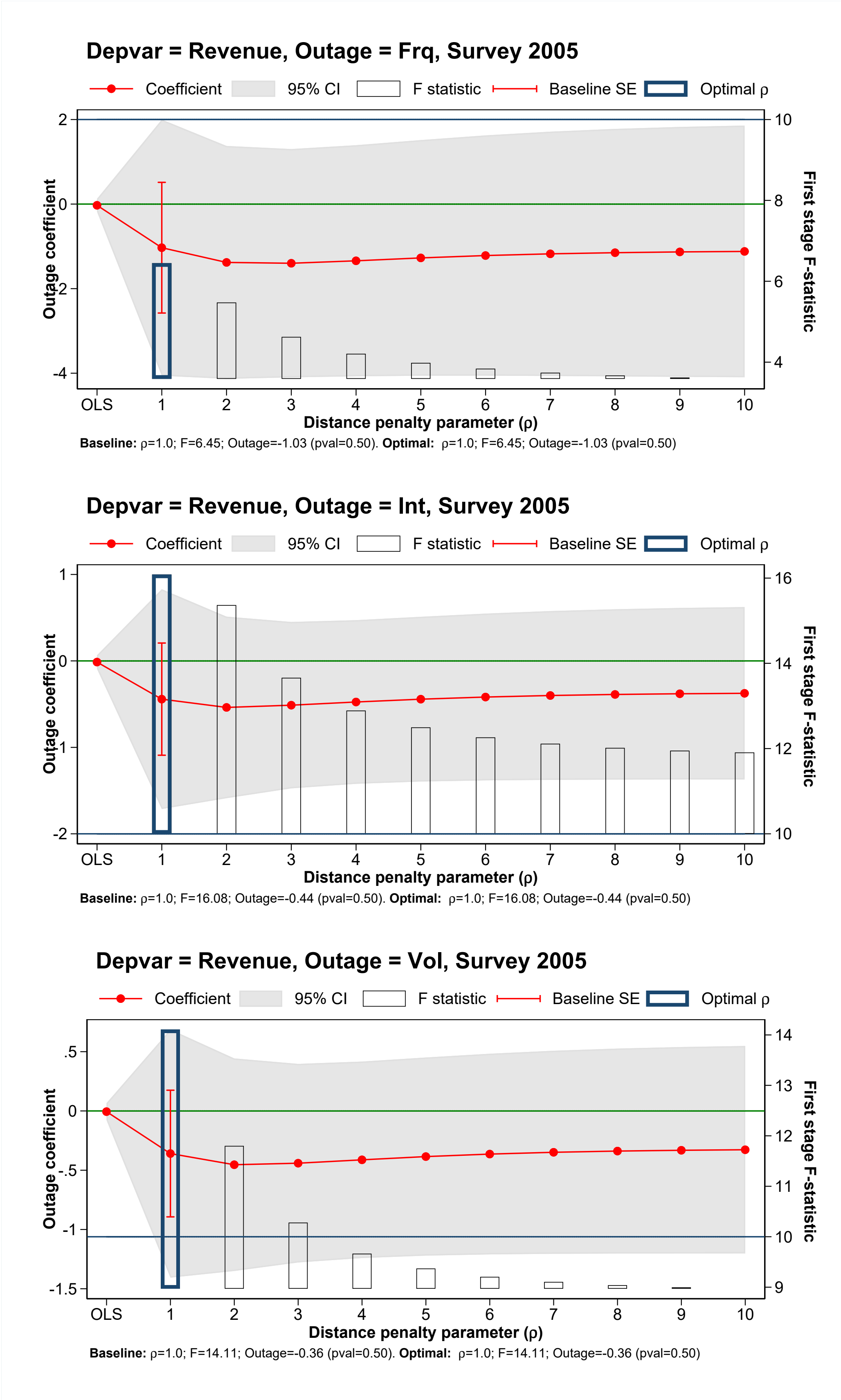
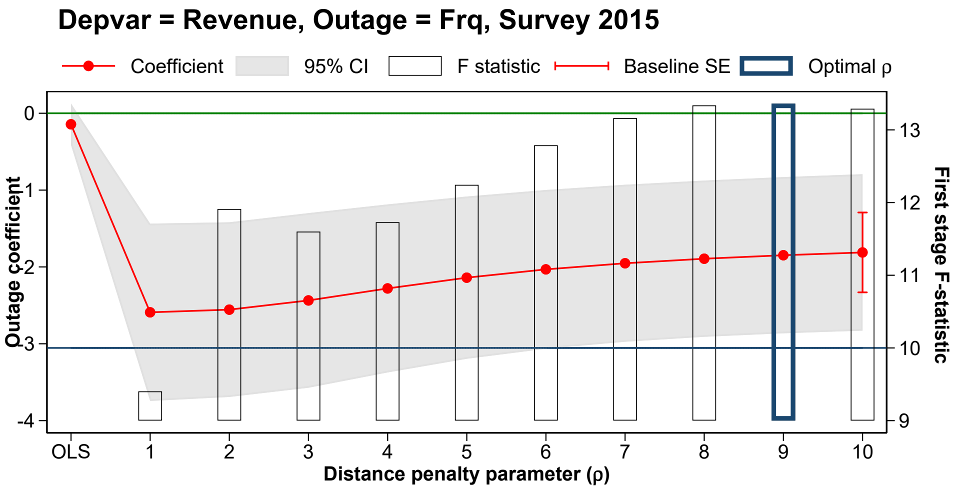
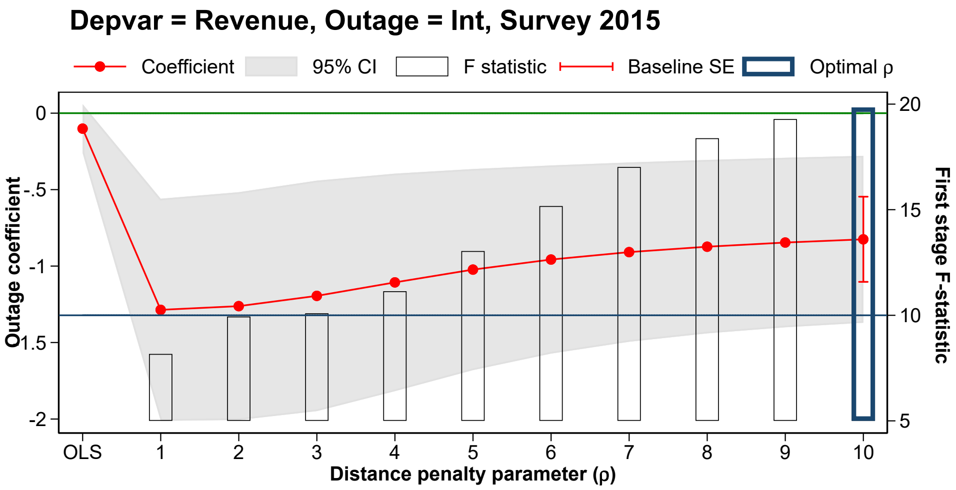

Outage = Vol, Survey 2015
rho*=10; F*=17.68; HAI* = -1.76; P-value*=0.000
Coefficient
95% Confidence interval
F statistic
HAI (IV) coefficient
F-statistic
Distance penalty parameter (ρ)

**Figure 2.5: Distance penalty parameter uncertainty analysis**

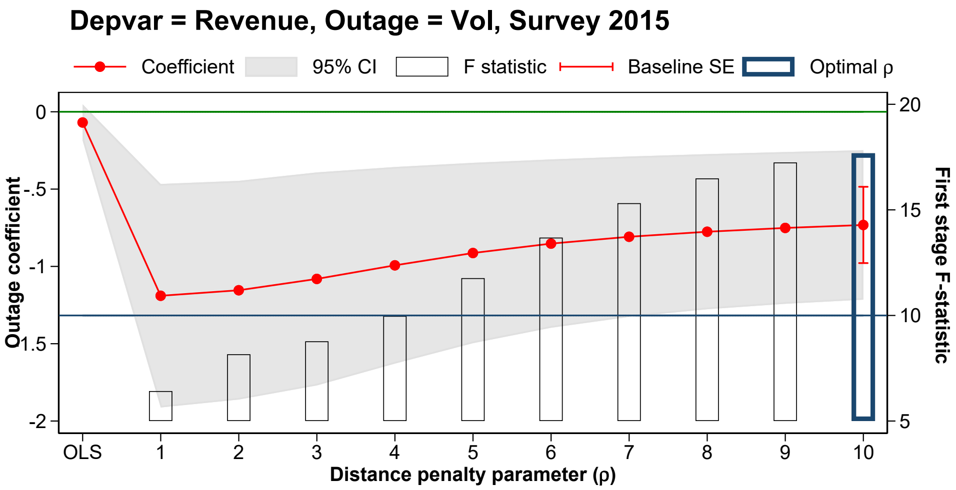





**Baseline:** ρ=10.0; F=13.29; Outage=-1.81 (pval=0.00). **Optimal:** ρ=9.0; F=13.36; Outage=-1.85 (pval=0.00)




**Baseline:** ρ=10.0; F=19.84; Outage=-0.82 (pval=0.00). **Optimal:** ρ=10.0; F=19.84; Outage=-0.82 (pval=0.00)




**Baseline:** ρ=10.0; F=17.68; Outage=-0.73 (pval=0.00). **Optimal:** ρ=10.0; F=17.68; Outage=-0.73 (pval=0.00)

# Tables

## Table 2.1: Summary statistics

| | Survey 2005 | | | | | Survey 2015 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | N | mean | sd | min | max | N | mean | sd | min | max |
| **PROVINCE LEVEL DATA** | | | | | | | | | | |
| **Province characteristics** | | | | | | | | | | |
| Elevation (m) | 24 | 128 | 154 | 1.94 | 464 | 19 | 119 | 142 | 1.94 | 397 |
| Rainfall shocks (SPI) | 24 | 0.080 | 0.63 | -1.35 | 0.76 | 19 | -0.35 | 0.38 | -0.95 | 0.46 |
| Cooling degree (F) | 24 | 11.9 | 2.95 | 7.20 | 15.8 | 19 | 11.6 | 2.60 | 7.90 | 15.4 |
| Province IP share | 24 | 0.033 | 0.058 | 0.0016 | 0.25 | 19 | 0.042 | 0.049 | 0.0051 | 0.18 |
| Province IP Index | 24 | 1.18 | 0.053 | 1.08 | 1.32 | 19 | 1.07 | 0.057 | 0.88 | 1.15 |
| | | | | | | | | | | |
| **FIRM LEVEL DATA** | | | | | | | | | | |
| **Power provision** | | | | | | | | | | |
| Power outages; frequency (occurences per month) | 1,150 | 0.60 | 1.20 | 0 | 20 | 960 | 0.37 | 1.19 | 0 | 20 |
| Power outages;intensity (hours per occurence) | 1,149 | 2.51 | 8.56 | 0 | 96 | 960 | 1.46 | 5.82 | 0 | 96 |
| Power outages; volume (hours per month) | 1,149 | 4.61 | 20.7 | 0 | 384 | 960 | 3.12 | 18.7 | 0 | 480 |
| Generator ownership or share; binary | 1,131 | 0.34 | 0.47 | 0 | 1 | 684 | 0.35 | 0.48 | 0 | 1 |
| **Firm characteristics** | | | | | | | | | | |
| Firm age | 1,147 | 12.5 | 13.2 | 1 | 115 | 989 | 13.3 | 10.3 | 1 | 113 |
| Small size | 1,149 | 0.10 | 0.30 | 0 | 1 | 989 | 0.38 | 0.49 | 0 | 1 |
| Medium size | 1,149 | 0.37 | 0.48 | 0 | 1 | 989 | 0.35 | 0.48 | 0 | 1 |
| Large size | 1,149 | 0.26 | 0.44 | 0 | 1 | 989 | 0.17 | 0.38 | 0 | 1 |
| Very large size | 1,149 | 0.27 | 0.45 | 0 | 1 | 989 | 0.098 | 0.30 | 0 | 1 |
| State ownership 10%-50% | 1,145 | 0.14 | 0.34 | 0 | 1 | 994 | 0.020 | 0.14 | 0 | 1 |
| State ownership > 50% | 1,145 | 0.20 | 0.40 | 0 | 1 | 994 | 0.015 | 0.12 | 0 | 1 |
| Foreign ownership 10%-50% | 1,145 | 0.017 | 0.13 | 0 | 1 | 993 | 0.013 | 0.11 | 0 | 1 |
| Foreign ownership > 50% | 1,145 | 0.100 | 0.30 | 0 | 1 | 993 | 0.065 | 0.25 | 0 | 1 |
| Share-holding | 1,149 | 0.37 | 0.48 | 0 | 1 | 989 | 0.22 | 0.41 | 0 | 1 |
| Share-traded | 1,149 | 0.0035 | 0.059 | 0 | 1 | 989 | 0.039 | 0.19 | 0 | 1 |
| Exporter | 1,150 | 0.46 | 0.50 | 0 | 1 | 994 | 0.27 | 0.45 | 0 | 1 |
| Access to credit | 1,150 | 0.70 | 0.46 | 0 | 1 | 971 | 0.49 | 0.50 | 0 | 1 |
| **Firm performance** | | | | | | | | | | |
| Revenues (bil. VND) | 1,141 | 129 | 333 | 0.16 | 5,271 | 975 | 72.8 | 228 | 0.034 | 4,108 |
| TFP YKL model; log | 986 | 2.34 | 1.23 | -1.76 | 6.57 | 432 | 2.34 | 1.37 | -1.35 | 7.57 |
| TFP YKLM model; log | 975 | 1.43 | 0.84 | -1.52 | 3.92 | 401 | 1.89 | 1.10 | -0.44 | 5.85 |
| **Energy use** | | | | | | | | | | |
| Generator use; % electricity | 1,045 | 1.37 | 3.51 | 0 | 25 | 637 | 0.37 | 0.80 | 0 | 7 |
| Energy cost (mil. VND) | 1,146 | 2,854 | 9,659 | 1.14 | 128,264 | | | | | |
| Fuel cost (mil. VND) | | | | | | 476 | 4,271 | 40,972 | 0.68 | 753,043 |
| Electricity cost (mil. VND) | | | | | | 892 | 681 | 2,387 | 0.68 | 34,229 |
| **Other factor use** | | | | | | | | | | |
| Material cost (bil. VND) | 1,134 | 97.4 | 299 | 0.036 | 5,808 | 552 | 63.7 | 447 | 0.0034 | 9,844 |
| Labor cost (bil. VND) | 1,139 | 10.7 | 23.0 | 0.023 | 324 | 899 | 5.75 | 16.2 | 0.010 | 222 |
| Earning/labor (mil.VND) | 485 | 23.1 | 17.1 | 1.82 | 173 | 876 | 38.5 | 45.0 | 0.89 | 430 |

**Table 2.2: The impact of outages on firm revenue(OLS estimates)**

| | Survey 2005 | | | Survey 2015 | | |
|---|---|---|---|---|---|---|
| VARIABLES | *Frq* | *Int* | *Vol* | *Frq* | *Int* | *Vol* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Revenue; log** | | | | | | |
| Power outage; log | -0.03 | -0.01 | -0.01 | -0.14 | -0.10 | -0.07 |
| | (0.07) | (0.04) | (0.04) | (0.13) | (0.08) | (0.06) |
| Age; log | 0.09** | 0.09** | 0.09** | 0.05 | 0.05 | 0.05 |
| | (0.04) | (0.04) | (0.04) | (0.08) | (0.08) | (0.08) |
| Medium size | 0.79*** | 0.78*** | 0.78*** | 1.50*** | 1.50*** | 1.50*** |
| | (0.13) | (0.13) | (0.13) | (0.10) | (0.10) | (0.10) |
| Large size | 1.97*** | 1.96*** | 1.97*** | 2.70*** | 2.71*** | 2.70*** |
| | (0.18) | (0.18) | (0.18) | (0.20) | (0.20) | (0.20) |
| Very large size | 3.13*** | 3.13*** | 3.13*** | 3.89*** | 3.90*** | 3.89*** |
| | (0.22) | (0.22) | (0.22) | (0.20) | (0.19) | (0.20) |
| State ownership 10%-50% | 0.28** | 0.28** | 0.29** | -0.09 | -0.09 | -0.09 |
| | (0.11) | (0.11) | (0.11) | (0.32) | (0.32) | (0.32) |
| State ownership > 50% | 0.66*** | 0.66*** | 0.66*** | 0.50* | 0.52* | 0.51* |
| | (0.15) | (0.15) | (0.15) | (0.25) | (0.25) | (0.25) |
| Foreign ownership 10%-50% | 0.70** | 0.70** | 0.70** | 0.23 | 0.22 | 0.23 |
| | (0.25) | (0.25) | (0.25) | (0.33) | (0.33) | (0.33) |
| Foreign ownership > 50% | 0.73*** | 0.73*** | 0.73*** | 0.49*** | 0.49*** | 0.49*** |
| | (0.23) | (0.23) | (0.23) | (0.12) | (0.12) | (0.12) |
| Share-holding | 0.20** | 0.20** | 0.20** | 0.39** | 0.38** | 0.38** |
| | (0.09) | (0.09) | (0.09) | (0.16) | (0.16) | (0.16) |
| Share-traded | 0.71** | 0.71** | 0.72** | 0.45* | 0.44* | 0.44* |
| | (0.28) | (0.28) | (0.28) | (0.23) | (0.22) | (0.22) |
| Exporter | 0.20*** | 0.20*** | 0.20*** | -0.14* | -0.14* | -0.14* |
| | (0.06) | (0.06) | (0.06) | (0.08) | (0.08) | (0.08) |
| Access to credit | 0.55*** | 0.55*** | 0.55*** | 0.06 | 0.05 | 0.05 |
| | (0.07) | (0.08) | (0.08) | (0.16) | (0.16) | (0.16) |
| IP share | 0.84 | 0.85 | 0.85 | 7.03*** | 7.04*** | 7.03*** |
| | (0.72) | (0.73) | (0.73) | (1.26) | (1.26) | (1.27) |
| IP index | -0.21 | -0.20 | -0.20 | 1.94 | 1.93 | 1.94 |
| | (0.89) | (0.90) | (0.90) | (1.32) | (1.28) | (1.29) |
| Cooling degree; log | 0.39 | 0.39 | 0.39 | 0.03 | 0.03 | 0.03 |
| | (0.32) | (0.32) | (0.32) | (0.14) | (0.13) | (0.14) |
| Elevation (km); log | -0.10** | -0.10** | -0.09** | 0.04 | 0.05 | 0.04 |
| | (0.04) | (0.04) | (0.04) | (0.03) | (0.03) | (0.03) |
| Rainfall shocks (SPI) | 0.04 | 0.04 | 0.04 | 0.03 | 0.02 | 0.02 |
| | (0.09) | (0.09) | (0.09) | (0.13) | (0.12) | (0.12) |
| R-squared | 0.60 | 0.60 | 0.60 | 0.48 | 0.48 | 0.48 |
| Observations | 1,133 | 1,132 | 1,132 | 915 | 915 | 915 |

The regression includes dummies for sectors. The dependent variable in bold. Robust standard errors clustered at province level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Three measures of power outages (in log form) indicated in each column name: *Frq* - Frequency (average number of outage per month); *Int* - Intensity (average duration (hour) per outage); and *Vol* - Volume (average outage hour per month = *Frq*× *Int*).

**Table 2.3: Impact of power outages on TFP and other inputs (OLS estimates)**

| VARIABLES | Survey 2005 | | | Survey 2015 | | |
|---|---|---|---|---|---|---|
| | *Frq* | *Int* | *Vol* | *Frq* | *Int* | *Vol* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | | | **Panel A: TFPR** | | | |
| **TFP YKL model; log** | | | | | | |
| Power outage; log | -0.15*** | -0.06* | -0.05** | -0.12 | -0.04 | -0.03 |
| | (0.05) | (0.03) | (0.02) | (0.16) | (0.09) | (0.07) |
| R-squared | 0.07 | 0.07 | 0.07 | 0.10 | 0.10 | 0.10 |
| Observations | 978 | 977 | 977 | 421 | 421 | 421 |
| **TFP YKLM model; log** | | | | | | |
| Power outage; log | -0.03 | -0.01 | -0.01 | -0.01 | 0.01 | 0.00 |
| | (0.02) | (0.01) | (0.01) | (0.09) | (0.05) | (0.04) |
| R-squared | 0.02 | 0.02 | 0.02 | 0.06 | 0.06 | 0.06 |
| Observations | 967 | 966 | 966 | 392 | 392 | 392 |
| | | | **Panel B: Energy inputs** | | | |
| **Generator use; log** | | | | | | |
| Power outage; log | 0.17*** | 0.08*** | 0.09*** | 0.11*** | 0.08*** | 0.05*** |
| | (0.06) | (0.02) | (0.02) | (0.04) | (0.02) | (0.01) |
| R-squared | 0.10 | 0.10 | 0.11 | 0.16 | 0.18 | 0.17 |
| Observations | 1,036 | 1,035 | 1,035 | 605 | 605 | 605 |
| **Energy cost; log** | | | | | | |
| Power outage; log | 0.17 | 0.00 | 0.01 | | | |
| | (0.12) | (0.05) | (0.04) | | | |
| R-squared | 0.37 | 0.36 | 0.36 | | | |
| Observations | 1,137 | 1,136 | 1,136 | | | |
| **Electric cost; log** | | | | | | |
| Power outage; log | | | | 0.11 | 0.06 | 0.06 |
| | | | | (0.10) | (0.04) | (0.03) |
| R-squared | | | | 0.40 | 0.40 | 0.40 |
| Observations | | | | 841 | 841 | 841 |
| **Fuel cost; log** | | | | | | |
| Power outage; log | | | | -0.26 | -0.08 | -0.09 |
| | | | | (0.21) | (0.12) | (0.09) |
| R-squared | | | | 0.31 | 0.31 | 0.31 |
| Observations | | | | 458 | 458 | 458 |
| | | | **Panel C: Other inputs** | | | |
| **Material cost; log** | | | | | | |
| Power outage; log | -0.03 | -0.02 | -0.01 | -0.19 | -0.14 | -0.09 |
| | (0.10) | (0.05) | (0.04) | (0.19) | (0.13) | (0.09) |

*(cont.)*

| VARIABLES | Survey 2005 | | | Survey 2015 | | |
|---|---|---|---|---|---|---|
| | *Frq* | *Int* | *Vol* | *Frq* | *Int* | *Vol* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| R-squared | 0.50 | 0.50 | 0.50 | 0.40 | 0.40 | 0.40 |
| Observations | 1,125 | 1,124 | 1,124 | 529 | 529 | 529 |
| **Labor cost; log** | | | | | | |
| Power outage; log | 0.04 | 0.01 | 0.01 | 0.02 | -0.00 | -0.00 |
| | (0.05) | (0.02) | (0.02) | (0.07) | (0.03) | (0.03) |
| R-squared | 0.76 | 0.76 | 0.76 | 0.57 | 0.57 | 0.57 |
| Observations | 1,130 | 1,129 | 1,129 | 845 | 845 | 845 |

The regressions include control variables as those in Table 2.2 (including sector dummies). Dependent variables are in bold. Three measures of power outages (in log form) indicated in each column name are *Frq* - Frequency (average number of outage per month); *Int* - Intensity (average duration (hour) per outage); and *Vol* - Volume (average outage hour per month = *Frq*× *Int*). Robust standard errors clustered at province level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

**Table 2.4: Hydropower generation model**

| VARIABLES | Average generation by month (MWh/day) |
|---|---|
| Installed capacity (MW) | 6.187*** |
| | (1.083) |
| Upstream installed capacity (MW) | 1.383** |
| | (0.608) |
| Inflow to dam; SWAT simulation ($m^3/s$) | 4.167*** |
| | (0.458) |
| Inflow to dam; SWAT simulation squared ($m^6/s^2$) | -0.000204** |
| | (8.63e-05) |
| Observations | 2,984 |
| R-squared | 0.878 |
| Number of groups | 40 |
| Dam FE | Y |

Driscoll-Kraay standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.5: **List of hydropower plants used to calculate IV**

| No. | Dam | Year of operation | Installed capacity (MW) | 2005 Survey | 2015 Survey |
|---|---|---|---|---|---|
| 1 | Da Nhim | 1964 | 160 | x | x |
| 2 | Thac Ba | 1971 | 120 | x | x |
| 3 | Tri An | 1991 | 400 | x | x |
| 4 | Hoa Binh | 1994 | 1920 | x | x |
| 5 | Vinh Son | 1994 | 66 | x | x |
| 6 | Thac Mo | 1995 | 150 | x | x |
| 7 | Song Hinh | 2000 | 70 | x | x |
| 8 | Yaly | 2000 | 720 | x | x |
| 9 | Da Mi | 2001 | 175 | x | x |
| 10 | Ham Thuan | 2001 | 300 | x | x |
| 11 | Can Don | 2003 | 78 | x | x |
| 12 | Sesan 3 | 2006 | 260 | | x |
| 13 | Quang Tri | 2007 | 64 | | x |
| 14 | A Vuong | 2008 | 210 | | x |
| 15 | Dai Ninh | 2008 | 300 | | x |
| 16 | Tuyen Quang | 2008 | 342 | | x |
| 17 | Binh Dien | 2009 | 44 | | x |
| 18 | Buon Kuop | 2009 | 280 | | x |
| 19 | Buon Tua Srah | 2009 | 86 | | x |
| 20 | Plei Krong 1 | 2009 | 100 | | x |
| 21 | Sesan 4 | 2009 | 360 | | x |
| 22 | Song Ba Ha | 2009 | 220 | | x |
| 23 | Song Con | 2009 | 63 | | x |
| 24 | Ban Ve | 2010 | 320 | | x |
| 25 | Cua Dat | 2010 | 97 | | x |
| 26 | Huong Dien | 2010 | 71 | | x |
| 27 | Son La | 2010 | 2400 | | x |
| 28 | Song Tranh 2 | 2010 | 190 | | x |
| 29 | Srepok 3 | 2010 | 220 | | x |
| 30 | An Khe - Kanak | 2011 | 173 | | x |
| 31 | Dak R'Tih | 2011 | 144 | | x |
| 32 | Dong Nai 3 | 2011 | 180 | | x |
| 33 | A Luoi | 2012 | 170 | | x |
| 34 | Bac Ha | 2012 | 90 | | x |
| 35 | Dak Mi 4 | 2012 | 190 | | x |
| 36 | Dong Nai 4 | 2012 | 340 | | x |
| 37 | Ban Chat | 2013 | 220 | | x |
| 38 | Hua Na | 2013 | 180 | | x |
| 39 | Khe Bo | 2013 | 100 | | x |
| 40 | Nam Chien | 2013 | 200 | | x |

*Note:* x indicates that the corresponding plants was used to construct IV in the given survey. Surveys capture the data of firm performance one year before.

**Table 2.6: Summary statistics of instrumental variables $HAI(\rho)$**

| | 2005 Survey | | | | | | 2015 Survey | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\rho$ | mean | sd | median | min | max | N | mean | sd | median | min | max | N |
| $\rho$ =1 | 0.460 | 0.0145 | 0.458 | 0.442 | 0.514 | 1141 | 0.437 | 0.0277 | 0.446 | 0.342 | 0.471 | 975 |
| $\rho$ =2 | 0.457 | 0.0319 | 0.455 | 0.428 | 0.592 | 1141 | 0.469 | 0.0667 | 0.486 | 0.302 | 0.559 | 975 |
| $\rho$ =3 | 0.458 | 0.0438 | 0.457 | 0.426 | 0.659 | 1141 | 0.491 | 0.0888 | 0.516 | 0.266 | 0.591 | 975 |
| $\rho$ =4 | 0.459 | 0.0499 | 0.458 | 0.424 | 0.693 | 1141 | 0.503 | 0.0992 | 0.524 | 0.248 | 0.599 | 975 |
| $\rho$ =5 | 0.460 | 0.0522 | 0.459 | 0.425 | 0.706 | 1141 | 0.510 | 0.105 | 0.526 | 0.235 | 0.601 | 975 |
| $\rho$ =6 | 0.460 | 0.0529 | 0.460 | 0.425 | 0.709 | 1141 | 0.513 | 0.108 | 0.528 | 0.226 | 0.601 | 975 |
| $\rho$ =7 | 0.460 | 0.0531 | 0.460 | 0.425 | 0.710 | 1141 | 0.516 | 0.111 | 0.528 | 0.220 | 0.601 | 975 |
| $\rho$ =8 | 0.460 | 0.0530 | 0.461 | 0.426 | 0.709 | 1141 | 0.518 | 0.112 | 0.529 | 0.216 | 0.601 | 975 |
| $\rho$ =9 | 0.460 | 0.0528 | 0.461 | 0.426 | 0.708 | 1141 | 0.519 | 0.113 | 0.529 | 0.213 | 0.601 | 975 |
| $\rho$ =10 | 0.460 | 0.0526 | 0.462 | 0.426 | 0.706 | 1141 | 0.520 | 0.113 | 0.529 | 0.212 | 0.601 | 975 |

*Note:* Table reports the summary statistics of IV $HAI(\rho)$ with varying distance penalty parameters $\rho$ of the sample including all observations with identified province and non-missing revenues after outlier-removal. See text for more details.

**Table 2.7: First stage for Revenue**

| | Survey 2005, $\rho$ = 1 | | | Survey 2015, $\rho$ = 10 | | |
|---|---|---|---|---|---|---|
| VARIABLES | *Frq* | *Int* | *Vol* | *Frq* | *Int* | *Vol* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| HAI($\rho$) | -4.34** | -9.39*** | -11.65*** | -0.71*** | -1.56*** | -1.76*** |
| | (1.76) | (2.09) | (3.08) | (0.19) | (0.35) | (0.42) |
| Age; log | -0.00 | 0.03 | 0.02 | -0.01 | 0.02 | 0.00 |
| | (0.02) | (0.04) | (0.04) | (0.03) | (0.03) | (0.05) |
| Medium size | 0.01 | -0.09 | -0.06 | 0.00 | 0.02 | 0.03 |
| | (0.06) | (0.12) | (0.14) | (0.04) | (0.06) | (0.09) |
| Large size | -0.03 | -0.13 | -0.12 | 0.01 | 0.07 | 0.05 |
| | (0.08) | (0.16) | (0.19) | (0.04) | (0.09) | (0.11) |
| Very large size | 0.01 | -0.11 | -0.09 | 0.08 | 0.22 | 0.20 |
| | (0.06) | (0.15) | (0.17) | (0.10) | (0.15) | (0.20) |
| State ownership 10%-50% | -0.04 | -0.05 | -0.04 | 0.11 | 0.20 | 0.27 |
| | (0.05) | (0.08) | (0.10) | (0.17) | (0.22) | (0.33) |
| State ownership > 50% | 0.01 | 0.01 | -0.00 | -0.07 | 0.06 | -0.01 |
| | (0.04) | (0.08) | (0.10) | (0.07) | (0.24) | (0.23) |
| Foreign ownership 10%-50% | 0.08 | 0.28 | 0.31 | -0.21*** | -0.43*** | -0.52*** |
| | (0.08) | (0.21) | (0.24) | (0.07) | (0.08) | (0.11) |
| Foreign ownership > 50% | -0.01 | 0.01 | -0.01 | -0.01 | -0.05 | -0.05 |
| | (0.05) | (0.09) | (0.11) | (0.07) | (0.13) | (0.16) |
| Share-holding | 0.05 | 0.05 | 0.06 | -0.04 | -0.11** | -0.10 |
| | (0.04) | (0.06) | (0.07) | (0.03) | (0.05) | (0.07) |
| Share-traded | -0.31*** | -0.71*** | -0.89*** | 0.01 | -0.12 | -0.11 |
| | (0.11) | (0.22) | (0.24) | (0.14) | (0.18) | (0.28) |
| Exporter | -0.02 | -0.01 | -0.03 | 0.03 | 0.00 | 0.04 |
| | (0.03) | (0.05) | (0.06) | (0.05) | (0.09) | (0.12) |
| Access to credit | 0.12*** | 0.19*** | 0.26*** | 0.02 | -0.03 | 0.00 |
| | (0.03) | (0.06) | (0.07) | (0.03) | (0.05) | (0.06) |
| IP share | -0.33 | -0.43 | -0.71 | -0.02 | 0.24 | -0.02 |
| | (0.23) | (0.41) | (0.50) | (0.32) | (0.58) | (0.75) |
| IP index | 0.21 | 0.74 | 0.80 | -0.96* | -1.90** | -2.24* |
| | (0.53) | (0.85) | (1.09) | (0.51) | (0.93) | (1.15) |
| Cooling degree; log | 0.16* | 0.41*** | 0.50*** | 0.22*** | 0.36** | 0.45** |
| | (0.08) | (0.10) | (0.13) | (0.08) | (0.16) | (0.21) |
| Elevation (km); log | -0.03 | -0.04 | -0.04 | -0.03** | -0.06* | -0.08** |
| | (0.02) | (0.03) | (0.04) | (0.02) | (0.03) | (0.04) |
| Rainfall shocks (SPI) | 0.01 | 0.02 | 0.04 | 0.04 | -0.02 | 0.02 |
| | (0.05) | (0.07) | (0.09) | (0.06) | (0.11) | (0.15) |
| Observations | 1,133 | 1,132 | 1,132 | 915 | 915 | 915 |
| Clusters | 24 | 24 | 24 | 19 | 19 | 19 |
| First stage F-statistic | 6.08 | 20.12 | 14.32 | 13.29 | 19.84 | 17.68 |
| SW $\chi^2$ test | 6.56** | 21.73*** | 15.46*** | 14.69*** | 21.93*** | 19.54*** |

The table reports the results for the first stage of our 2SLS estimates, which include dummies for sectors. The dependent variable in the second stage is in bold. The endogenous variable in the second stage is a measure of power outages as indicated in each column name, which could be *Frq* - Frequency (average number of outage per month); *Int* - Intensity (average duration (hour) per outage); or *Vol* - Volume (average outage hour per month = *Frq*× *Int*). The first stage F-statistic reported is the Kleibergen-Paap rk Wald F-statistic that is robust to heteroskedasticity. SW $\chi^2$ test is the Sanderson-Windmeijer first stage $\chi^2$ test for underidentification. Robust standard errors clustered at province level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

## Table 2.8: First stage for TFP and other inputs

| VARIABLES | Survey 2005, $\rho$ = 1 | | | Survey 2015, $\rho$ = 10 | | |
|---|---|---|---|---|---|---|
| | *Frq* | *Int* | *Vol* | *Frq* | *Int* | *Vol* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | | | **Panel A: TFPR** | | | |
| **TFP YKL model; log** | | | | | | |
| HAI($\rho$); IV | -3.83** | -9.56*** | -11.53*** | -0.62* | -1.46** | -1.53* |
| | (1.78) | (2.67) | (3.72) | (0.35) | (0.61) | (0.80) |
| Observations | 978 | 977 | 977 | 421 | 421 | 421 |
| Clusters | 24 | 24 | 24 | 19 | 19 | 19 |
| F-statistic | 4.61 | 12.85 | 9.59 | 3.15 | 5.68 | 3.62 |
| SW $\chi^2$ test | 4.98** | 13.88*** | 10.36*** | 3.61* | 6.50** | 4.15** |
| **TFP YKLM model; log** | | | | | | |
| HAI($\rho$); IV | -3.87** | -9.52*** | -11.54*** | -0.61 | -1.44** | -1.50 |
| | (1.82) | (2.78) | (3.84) | (0.40) | (0.68) | (0.91) |
| Observations | 967 | 966 | 966 | 392 | 392 | 392 |
| Clusters | 24 | 24 | 24 | 19 | 19 | 19 |
| F-statistic | 4.54 | 11.69 | 9.01 | 2.25 | 4.45 | 2.71 |
| SW $\chi^2$ test | 4.90** | 12.63*** | 9.73*** | 2.60 | 5.13** | 3.13* |
| | | | **Panel B: Energy inputs** | | | |
| **Generator use; log** | | | | | | |
| HAI($\rho$); IV | -4.49** | -10.61*** | -12.88*** | -0.75*** | -1.71*** | -1.86*** |
| | (1.84) | (2.75) | (3.82) | (0.26) | (0.46) | (0.58) |
| Observations | 1,036 | 1,035 | 1,035 | 605 | 605 | 605 |
| Clusters | 24 | 24 | 24 | 19 | 19 | 19 |
| F-statistic | 5.95 | 14.85 | 11.38 | 8.20 | 13.67 | 10.14 |
| SW $\chi^2$ test | 6.42** | 16.02*** | 12.28*** | 9.17*** | 15.28*** | 11.34*** |
| **Energy cost; log** | | | | | | |
| HAI($\rho$); IV | -4.53*** | -10.04*** | -12.19*** | | | |
| | (1.73) | (2.00) | (3.00) | | | |
| Observations | 1,137 | 1,136 | 1,136 | | | |
| Clusters | 24 | 24 | 24 | | | |
| F-statistic | 6.82 | 25.16 | 16.47 | | | |
| SW $\chi^2$ test | 7.36*** | 27.16*** | 17.78*** | | | |
| **Electric cost; log** | | | | | | |
| HAI($\rho$); IV | | | | -0.78*** | -1.62*** | -1.85*** |
| | | | | (0.19) | (0.35) | (0.42) |
| Observations | | | | 841 | 841 | 841 |
| Clusters | | | | 19 | 19 | 19 |
| F-statistic | | | | 17.13 | 20.89 | 19.32 |
| SW $\chi^2$ test | | | | 19.01*** | 23.18*** | 21.44*** |
| **Fuel cost; log** | | | | | | |
| HAI($\rho$); IV | | | | -1.16*** | -2.17*** | -2.42*** |
| | | | | (0.26) | (0.52) | (0.66) |
| Observations | | | | 458 | 458 | 458 |
| Clusters | | | | 19 | 19 | 19 |
| F-statistic | | | | 20.15 | 17.52 | 13.59 |
| SW $\chi^2$ test | | | | 23.09*** | 20.07*** | 15.57*** |
| | | | **Panel C: Other inputs** | | | |

*(cont.)*

| VARIABLES | Survey 2005, $\rho$ = 1 | | | Survey 2015, $\rho$ = 10 | | |
|---|---|---|---|---|---|---|
| | *Frq* | *Int* | *Vol* | *Frq* | *Int* | *Vol* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Material cost; log** | | | | | | |
| HAI($\rho$); IV | -4.25** | -9.32*** | -11.52*** | -0.83*** | -1.72*** | -1.87*** |
| | (1.72) | (2.15) | (3.12) | (0.27) | (0.48) | (0.63) |
| Observations | 1,125 | 1,124 | 1,124 | 529 | 529 | 529 |
| Clusters | 24 | 24 | 24 | 19 | 19 | 19 |
| F-statistic | 6.12 | 18.83 | 13.63 | 9.29 | 13.03 | 8.85 |
| SW $\chi^2$ test | 6.61** | 20.34*** | 14.72*** | 10.53*** | 14.76*** | 10.03*** |
| **Labor cost; log** | | | | | | |
| HAI($\rho$); IV | -4.20** | -9.28*** | -11.37*** | -0.68*** | -1.43*** | -1.62*** |
| | (1.73) | (2.11) | (3.10) | (0.19) | (0.36) | (0.43) |
| Observations | 1,130 | 1,129 | 1,129 | 845 | 845 | 845 |
| Clusters | 24 | 24 | 24 | 19 | 19 | 19 |
| F-statistic | 5.90 | 19.32 | 13.45 | 12.41 | 16.07 | 14.10 |
| SW $\chi^2$ test | 6.37** | 20.86*** | 14.52*** | 13.77*** | 17.82*** | 15.64*** |

Table reports the results for the first stage of our 2SLS estimates, which include control variables as those in Table 2.7 and dummies for sectors. The dependent variable in the second stage is in bold. The endogenous variable in the second stage is a measure of power outages as indicated in each column name, which could be *Frq* - Frequency (average number of outage per month); *Int* - Intensity (average duration (hour) per outage); or *Vol* - Volume (average outage hour per month = *Frq*× *Int*). The first stage F-statistic reported is the Kleibergen-Paap rk Wald F-statistic that is robust to heteroskedasticity. SW $\chi^2$ test is the Sanderson-Windmeijer first stage $\chi^2$ test for underidentification. Robust standard errors clustered at province level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

## Table 2.9: Impacts of Outages of Firm Revenues (2SLS estimates)

| | Survey 2005, $\rho$ = 1 | | | Survey 2015, $\rho$ = 10 | | |
|---|---|---|---|---|---|---|
| VARIABLES | *Frq* | *Int* | *Vol* | *Frq* | *Int* | *Vol* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Revenue; log** | | | | | | |
| Outage; 2SLS | -0.74 | -0.34 | -0.27 | -1.81*** | -0.82*** | -0.73*** |
| | (1.21) | (0.54) | (0.44) | (0.52) | (0.28) | (0.25) |
| Age; log | 0.09* | 0.10* | 0.10* | 0.04 | 0.08 | 0.06 |
| | (0.05) | (0.05) | (0.05) | (0.09) | (0.08) | (0.09) |
| Medium size | 0.79*** | 0.75*** | 0.76*** | 1.48*** | 1.49*** | 1.50*** |
| | (0.13) | (0.13) | (0.13) | (0.10) | (0.09) | (0.10) |
| Large size | 1.94*** | 1.92*** | 1.93*** | 2.69*** | 2.73*** | 2.71*** |
| | (0.21) | (0.21) | (0.20) | (0.22) | (0.22) | (0.22) |
| Very large size | 3.13*** | 3.09*** | 3.10*** | 3.98*** | 4.01*** | 3.98*** |
| | (0.20) | (0.22) | (0.21) | (0.25) | (0.20) | (0.22) |
| State ownership 10%-50% | 0.26** | 0.27** | 0.27*** | 0.08 | 0.05 | 0.08 |
| | (0.12) | (0.11) | (0.11) | (0.39) | (0.33) | (0.36) |
| State ownership > 50% | 0.67*** | 0.67*** | 0.67*** | 0.41 | 0.59* | 0.53* |
| | (0.14) | (0.14) | (0.14) | (0.29) | (0.32) | (0.31) |
| Foreign ownership 10%-50% | 0.76*** | 0.80** | 0.78** | -0.09 | -0.07 | -0.09 |
| | (0.29) | (0.33) | (0.31) | (0.35) | (0.32) | (0.34) |
| Foreign ownership > 50% | 0.72*** | 0.74*** | 0.73*** | 0.46*** | 0.44*** | 0.44*** |
| | (0.25) | (0.24) | (0.24) | (0.12) | (0.08) | (0.09) |
| Share-holding | 0.24** | 0.22** | 0.22** | 0.34** | 0.31* | 0.33** |
| | (0.11) | (0.09) | (0.09) | (0.16) | (0.16) | (0.17) |
| Share-traded | 0.50 | 0.49 | 0.49 | 0.48 | 0.36 | 0.38 |
| | (0.38) | (0.39) | (0.39) | (0.33) | (0.25) | (0.29) |
| Exporter | 0.18*** | 0.20*** | 0.19*** | -0.09 | -0.14 | -0.11 |
| | (0.06) | (0.06) | (0.06) | (0.11) | (0.11) | (0.12) |
| Access to credit | 0.63*** | 0.61*** | 0.62*** | 0.12 | 0.06 | 0.08 |
| | (0.16) | (0.11) | (0.12) | (0.16) | (0.16) | (0.16) |
| IP share | 0.66 | 0.76 | 0.71 | 6.66*** | 6.88*** | 6.67*** |
| | (0.69) | (0.71) | (0.70) | (0.86) | (1.06) | (1.08) |
| IP index | -0.03 | 0.07 | 0.03 | 1.24 | 1.42 | 1.35 |
| | (1.03) | (1.14) | (1.10) | (1.41) | (1.23) | (1.30) |
| Cooling degree; log | 0.49** | 0.51** | 0.51** | 0.28* | 0.18 | 0.21 |
| | (0.23) | (0.24) | (0.24) | (0.15) | (0.16) | (0.17) |
| Elevation (m); log | -0.12* | -0.11** | -0.11** | 0.03 | 0.04* | 0.04 |
| | (0.06) | (0.06) | (0.06) | (0.02) | (0.03) | (0.03) |
| Rainfall shocks (SPI) | 0.09 | 0.09 | 0.10 | 0.04 | -0.05 | -0.02 |
| | (0.11) | (0.11) | (0.11) | (0.12) | (0.12) | (0.13) |
| *Outage; OLS* | -0.03 | -0.01 | -0.01 | -0.14 | -0.10 | -0.07 |
| | (0.07) | (0.04) | (0.04) | (0.13) | (0.08) | (0.06) |
| Observations | 1,133 | 1,132 | 1,132 | 915 | 915 | 915 |
| Clusters | 24 | 24 | 24 | 19 | 19 | 19 |
| First stage F-statistic | 6.08 | 20.12 | 14.32 | 13.29 | 19.84 | 17.68 |
| SW $\chi^2$ test | 6.56** | 21.73*** | 15.46*** | 14.69*** | 21.93*** | 19.54*** |
| AR $\chi^2$ test | 0.46 | 0.45 | 0.45 | 5.67** | 5.67** | 5.67** |

The regression includes dummies for sectors. The dependent variables are in bold. The endogenous variable is a measure of power outages as indicated in each column name, which could be *Frq* - Frequency (average number of outage per month); *Int* - Intensity (average duration (hour) per outage); or *Vol* - Volume (average outage hour per month = *Frq*× *Int*). The excluded IV is *HAI*($\rho$) with predetermined values of $\rho$ for each survey. The OLS estimate is included for comparison. **First stage F-statistic:** Kleibergen-Paap rk Wald F-statistic that is robust to heteroskedasticity. **Underidentification test:** SW $\chi^2$ test (Sanderson-Windmeijer first stage $\chi^2$ test). **Weak-instrument robust tests for significant endogenous variables** : AR $\chi^2$ test (Anderson-Rubin Wald $\chi^2$ test). Robust standard errors clustered at province level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.10: Impact of Outages on TFPR and other inputs (2SLS estimates)

| VARIABLES | Survey 2005, $\rho$ = 1 | | | Survey 2015, $\rho$ = 10 | | |
|---|---|---|---|---|---|---|
| | *Frq* | *Int* | *Vol* | *Frq* | *Int* | *Vol* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | | | **Panel A: TFPR** | | | |
| **TFP YKL model; log** | | | | | | |
| Outage; 2SLS | -0.77 | -0.31 | -0.25 | -1.36*** | -0.57** | -0.55** |
| | (0.67) | (0.25) | (0.22) | (0.47) | (0.25) | (0.23) |
| *Outage; OLS* | -0.15*** | -0.06* | -0.05** | -0.12 | -0.04 | -0.03 |
| | (0.05) | (0.03) | (0.02) | (0.16) | (0.09) | (0.07) |
| Observations | 978 | 977 | 977 | 421 | 421 | 421 |
| First stage F-statistic | 4.61 | 12.85 | 9.59 | 3.15 | 5.68 | 3.62 |
| SW $\chi^2$ test | 4.98** | 13.88*** | 10.36*** | 3.61* | 6.50** | 4.15** |
| AR $\chi^2$ test | 2.59 | 2.50 | 2.50 | 3.97** | 3.97** | 3.97** |
| **TFP YKLM model; log** | | | | | | |
| Outage; 2SLS | -0.38 | -0.15* | -0.13* | -1.30 | -0.55 | -0.53 |
| | (0.25) | (0.08) | (0.07) | (1.03) | (0.38) | (0.41) |
| *Outage; OLS* | -0.03 | -0.01 | -0.01 | -0.01 | 0.01 | 0 |
| | (0.02) | (0.01) | (0.01) | (0.09) | (0.05) | (0.04) |
| Observations | 967 | 966 | 966 | 392 | 392 | 392 |
| First stage F-statistic | 4.54 | 11.69 | 9.01 | 2.25 | 4.45 | 2.71 |
| SW $\chi^2$ test | 4.90** | 12.63*** | 9.73*** | 2.60 | 5.13** | 3.13* |
| AR $\chi^2$ test | 3.65* | 3.66* | 3.66* | 4.66** | 4.66** | 4.66** |
| | | | **Panel B: Energy inputs** | | | |
| **Generator use; log** | | | | | | |
| Outage; 2SLS | 1.02*** | 0.43*** | 0.35*** | 0.76*** | 0.33*** | 0.31*** |
| | (0.33) | (0.14) | (0.11) | (0.21) | (0.10) | (0.10) |
| *Outage; OLS* | 0.17*** | 0.08*** | 0.09*** | 0.11*** | 0.08*** | 0.05*** |
| | (0.06) | (0.02) | (0.02) | (0.04) | (0.02) | (0.01) |
| Observations | 1,036 | 1,035 | 1,035 | 605 | 605 | 605 |
| First stage F-statistic | 5.95 | 14.85 | 11.38 | 8.20 | 13.67 | 10.14 |
| SW $\chi^2$ test | 6.42** | 16.02*** | 12.28*** | 9.17*** | 15.28*** | 11.34*** |
| AR $\chi^2$ test | 8.16*** | 8.26*** | 8.26*** | 6.49** | 6.49** | 6.49** |
| **Energy cost; log** | | | | | | |
| Outage; 2SLS | -2.03* | -0.92** | -0.76** | | | |
| | (1.04) | (0.38) | (0.33) | | | |
| *Outage; OLS* | 0.17 | 0 | 0.01 | | | |
| | (0.12) | (0.05) | (0.04) | | | |
| Observations | 1,137 | 1,136 | 1,136 | | | |
| First stage F-statistic | 6.82 | 25.16 | 16.47 | | | |
| SW $\chi^2$ test | 7.36*** | 27.16*** | 17.78*** | | | |
| AR $\chi^2$ test | 7.40*** | 7.63*** | 7.63*** | | | |
| **Electric cost; log** | | | | | | |
| Outage; 2SLS | | | | -2.46** | -1.18** | -1.03** |
| | | | | (1.14) | (0.49) | (0.43) |
| *Outage; OLS* | | | | 0.11 | 0.06 | 0.06 |
| | | | | (0.10) | (0.04) | (0.03) |
| Observations | | | | 841 | 841 | 841 |
| First stage F-statistic | | | | 17.13 | 20.89 | 19.32 |
| SW $\chi^2$ test | | | | 19.01*** | 23.18*** | 21.44*** |

*(cont.)*

| VARIABLES | Survey 2005, $\rho$ = 1 | | | Survey 2015, $\rho$ = 10 | | |
|---|---|---|---|---|---|---|
| | *Frq* | *Int* | *Vol* | *Frq* | *Int* | *Vol* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| AR $\chi^2$ test | | | | 9.31*** | 9.31*** | 9.31*** |
| **Fuel cost; log** | | | | | | |
| Outage; 2SLS | | | | -1.31 | -0.70 | -0.62 |
| | | | | (1.16) | (0.59) | (0.55) |
| *Outage; OLS* | | | | -0.26 | -0.08 | -0.09 |
| | | | | (0.21) | (0.12) | (0.09) |
| Observations | | | | 458 | 458 | 458 |
| First stage F-statistic | | | | 20.15 | 17.52 | 13.59 |
| SW $\chi^2$ test | | | | 23.09*** | 20.07*** | 15.57*** |
| AR $\chi^2$ test | | | | 1.78 | 1.78 | 1.78 |
| | | | **Panel C: Other inputs** | | | |
| **Material cost; log** | | | | | | |
| Outage; 2SLS | -0.75 | -0.34 | -0.27 | -1.39 | -0.67 | -0.62 |
| | (1.89) | (0.85) | (0.70) | (0.88) | (0.42) | (0.40) |
| *Outage; OLS* | -0.03 | -0.02 | -0.01 | -0.19 | -0.14 | -0.09 |
| | (0.10) | (0.05) | (0.04) | (0.19) | (0.13) | (0.09) |
| Observations | 1,125 | 1,124 | 1,124 | 529 | 529 | 529 |
| First stage F-statistic | 6.12 | 18.83 | 13.63 | 9.29 | 13.03 | 8.85 |
| SW $\chi^2$ test | 6.61** | 20.34*** | 14.72*** | 10.53*** | 14.76*** | 10.03*** |
| AR $\chi^2$ test | 0.18 | 0.17 | 0.17 | 3.34* | 3.34* | 3.34* |
| **Labor cost; log** | | | | | | |
| Outage; 2SLS | 0.10 | 0.05 | 0.04 | -1.53 | -0.73 | -0.64 |
| | (0.50) | (0.23) | (0.18) | (1.28) | (0.58) | (0.52) |
| *Outage; OLS* | 0.04 | 0.01 | 0.01 | 0.02 | 0 | 0 |
| | (0.05) | (0.02) | (0.02) | (0.07) | (0.03) | (0.03) |
| Observations | 1,130 | 1,129 | 1,129 | 845 | 845 | 845 |
| First stage F-statistic | 5.90 | 19.32 | 13.45 | 12.41 | 16.07 | 14.10 |
| SW $\chi^2$ test | 6.37** | 20.86*** | 14.52*** | 13.77*** | 17.82*** | 15.64*** |
| AR $\chi^2$ test | 0.04 | 0.04 | 0.04 | 2.75* | 2.75* | 2.75* |

The regression include control variables as those in Table 2.9 and dummies for sectors. The dependent variables are in bold. The endogenous variable is a measure of power outages as indicated in each column name, which could be *Frq* - Frequency (average number of outage per month); *Int* - Intensity (average duration (hour) per outage); or *Vol* - Volume (average outage hour per month = *Frq*× *Int*). The excluded IV is *HAI*($\rho$) with predetermined values of $\rho$ for each survey. The OLS estimate is included for comparison. **First stage F-statistic:** Kleibergen-Paap rk Wald F-statistic that is robust to heteroskedasticity. **Underidentification test:** SW $\chi^2$ test (Sanderson-Windmeijer first stage $\chi^2$ test). **Weak-instrument robust tests for significant endogenous variables** : AR $\chi^2$ test (Anderson-Rubin Wald $\chi^2$ test). Robust standard errors clustered at province level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

## Table 2.11: Factor intensity: Survey 2005 vs Survey 2015, median regressor

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | | | | | Revenues; log | | | | |
| $\alpha_K$ | 0.20*** | 0.21*** | 0.18*** | 0.035*** | 0.041*** | 0.037*** | 0.028*** | 0.030*** | 0.029*** |
| | (0.025) | (0.026) | (0.024) | (0.0096) | (0.0099) | (0.010) | (0.0088) | (0.0092) | (0.0096) |
| $\alpha_K$ * Year 2015 | 0.18*** | 0.18*** | 0.16*** | 0.12*** | 0.12*** | 0.12*** | 0.098*** | 0.10*** | 0.095*** |
| | (0.040) | (0.042) | (0.037) | (0.016) | (0.016) | (0.016) | (0.015) | (0.016) | (0.016) |
| $\alpha_L$ | 0.81*** | 0.79*** | 0.84*** | 0.24*** | 0.23*** | 0.24*** | 0.23*** | 0.23*** | 0.21*** |
| | (0.031) | (0.032) | (0.029) | (0.014) | (0.014) | (0.015) | (0.013) | (0.013) | (0.014) |
| $\alpha_L$ * Year 2015 | -0.25*** | -0.21*** | -0.21*** | -0.0018 | -0.0098 | -0.0028 | -0.039* | -0.040* | -0.035 |
| | (0.050) | (0.051) | (0.046) | (0.021) | (0.022) | (0.022) | (0.022) | (0.023) | (0.024) |
| $\alpha_M$ | | | | 0.73*** | 0.73*** | 0.73*** | 0.70*** | 0.70*** | 0.71*** |
| | | | | (0.010) | (0.011) | (0.011) | (0.0096) | (0.010) | (0.011) |
| $\alpha_M$ * Year 2015 | | | | -0.15*** | -0.14*** | -0.14*** | -0.14*** | -0.13*** | -0.13*** |
| | | | | (0.015) | (0.016) | (0.016) | (0.015) | (0.015) | (0.016) |
| $\alpha_N$ | | | | | | | 0.053*** | 0.056*** | 0.056*** |
| | | | | | | | (0.0086) | (0.0090) | (0.0095) |
| $\alpha_N$ * Year 2015 | | | | | | | 0.050*** | 0.044** | 0.047** |
| | | | | | | | (0.019) | (0.020) | (0.020) |
| Observations | 1,440 | 1,440 | 1,440 | 1,398 | 1,398 | 1,398 | 1,343 | 1,343 | 1,343 |
| Year dummies | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Province dummies | N | Y | Y | N | Y | Y | N | Y | Y |
| Sector dummies | N | N | Y | N | N | Y | N | N | Y |
| $\sum \alpha_i$; 2005 | 1.02 | 1.00 | 1.02 | 1.00 | 1.00 | 1.00 | 1.01 | 1.01 | 1.01 |
| CRS F-stat 2005 | 0.48 | 0.03 | 0.85 | 0.28 | 0.13 | 0.03 | 2.31 | 1.94 | 1.04 |
| $\sum \alpha_i$ ;2015 | 0.94 | 0.97 | 0.97 | 0.98 | 0.98 | 0.98 | 0.99 | 0.99 | 0.99 |
| CRS F-stat 2015 | 2.74* | 0.59 | 1.13 | 2.98* | 3.27* | 3.27* | 1.31 | 0.67 | 0.62 |

*Note:* Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. CRS F-stat is the hypothesis test for constant return to scales by year $\left(\sum \alpha_i = 1\right)$. Input factors included in the regressions are: Machine values (K), labor cost (L), Material cost (M) and Energy cost (N)

## 2.A Appendix A: Firm-level Data Supplements

This appendix provides supplemental information about the raw data and our data cleaning process. For variables not mentioned below there was no assumptions made on missing or their extreme values.

It should be noted that the WBES applied the stratified random sampling method, which is superior to simple random sampling (i.e., estimates with proper weights could lead to higher precision). The population units are divided into strata (non-overlapping, homogeneous groups), before simple random samples are drawn within each stratum. There are 3 levels of stratification applied for Vietnam: industry, firm size, and region. In the 2015 Survey, firms were stratified into 7 industry groups (5 manufacturing, and 2 services industries); 3 size groups including small (5 to 19 employees), medium (20 to 99 employees), and large (100 or more employees);, and 4 region groups (Red River Delta, North Central Area, and Central Coastal Area, South East, and Mekong River Delta).[25] There is no accessible documentation on the sampling method in the 2005 Survey.[26] However, there are similarities in the distribution of firm size, region, and manufacturing sector (see below), which suggests that the three levels of stratification were also applied to the 2005 Survey. As the surveys were conducted in a two-stages, it is recommended that information from the first stage (screening by phone) should be replaced by more reliable information from the second stage (face-to-face interview with the mangers/owners) whenever possible.

[25] Food, and Beverages (ISIC Rev. 3.1 code 15), Garments (ISIC code 18), Non-metallic mineral products (ISIC code 26), Fabricated metal products (ISIC code 28), Other Manufacturing (ISIC codes 16,17, 19-25, 27, 29-37), Retail (ISIC code 52), and Other Services (ISIC codes 45, 50, 51, 55, 60-64, and 72).

[26] Nevertheless, 1.13% of firms recorded that their major product belongs to the service sector.

### 2.A.1 Firm Characteristics

#### 2.A.1.1 Location

Vietnam's administration is organised in a 3-tier system: province level, district level, and commune level.The highest tier (province level) is comprised of 63 units including 5 municipalities (centrally managed cities), namely Ha Noi, Ho Chi Minh City, Hai Phong, Da Nang, and Can Tho, and 58 provinces. The regional classification, although it has no official administrative impact, can be helpful for spatial analysis as it groups municipalities, and provinces that share common features in location, topography, terrain, climate, socio-economy. Accordingly, Vietnam can be divided into three parts (the North, the Central, and the South) or 8 regions (Northwest, Northeast, Red River Delta, North Central Coast, South Central Coast, Central Highlands, Southeast, and Mekong River Delta). Within the context of the WBES Surveys cities are referred to as municipalities. We use 'provinces' to indicate all province level administrative units (municipalities, and provinces).

The 2005 and 2015 surveys contain different variables for location. Survey 2005 has two variables for region, and province. The 2015 Survey only has a variable for region but no variable for province. However, they have an optional variable for location (*a3x*), which provides information on province, district and/or commune where a firm is located although the details vary across observation. The majority of firms provide information on province, and only a few firms provide details on district and/or commune. Therefore, we choose province as the spatial unit for analysis in our study. Since we can not find information on the location of 2 firms at the province level (*a3x* variable) in the 2015 Survey, we treat their location as 'unidentified', and exclude them from our analysis. The distribution of firms' locations is illustrated in Table 2.A1.

Out of the eight regions across the country only 5 were sampled in the surveys, namely, the Red River Delta, the North Central, the Coastal Central, the South East, and the Mekong River Delta. Among them, the Red River Delta together with the South East account for the majority of the enterprises in the surveys, reflecting their importance to the economy. More than 30% of firms are located in each of these two regions.

**[Table 2.A1 about here]**

There were some changes (splits and mergers) in administration between two surveys. The most prominent is the expansion of the capital city (Hanoi) in 2008.[27] As a large number of variables (see below) are constructed based on the centroids of provinces, one implication to our spatial analysis is that the centroid of Hanoi changes over two surveys. To generate centroid-based variables for firms in Hanoi in Survey 2015, we used a GIS map before the merge (in 2005), construct separate variables for Hanoi, and Ha Tay as if there were no merge, then weighted them by the industrial values just before the merge.[28] Another more simple method is just to calculate the centroid of Hanoi based on a new GIS map after the merge. However, this is less reliable as the appended parts are very large in area but less important in terms of economic activity.

[27]In 2008, the whole Ha Tay province, four communes in Hoa Binh province (Yen Trung, Yen Binh, Tien Xuan, and Dong Xuan of Luong Son district), and one district (Me Linh) of Vinh Phuc province were merged into the capital Hanoi.

[28]Gross output of industry at current prices by province in 2007 of Hanoi, and Ha Tay are 116,096.4, and 20,173.5 (billion VND). The weight applied is 1:0.1737. We ignore the rural areas that used to belong to Hoa Binh, and Vinh Phuc provinces, and latter appended to Hanoi.

#### 2.A.1.2 Sector

The main difference between our surveys is that the 2005 Survey looks only at manufacturing firms, which are classified into 17 sector groups.[29] The 2015 Survey includes both manufacturing, and service firms following the sector classification of ISIC revision 3.1.[30] We need to reclassify sectors for several reasons. First, the sector classification is inconsistent across surveys. Second, in the 2005 Survey, there are 95 firms (8.26 %) coded 20 ('Other') which is much larger than many other sector groups in the same year useful. The 2015 Survey assigned a firm to a sector as a result of screener questionnaires (based on the first stage of the survey on the phone) rather than a face-to-face interview with the Manager/Owner /Director of each establishment (in the second stage of the survey). Hence, it is possible that they contain inaccurate information on the main activity of teh firm. Hence, we define a sector of firm based on the the two first digits of the ISIC code of the main product in terms of revenue share (provided by the variable *d1a2* in the panel database), which were consistently collected in the face-to-face interview phase of all surveys. For observations whose variable was missing or out of the standard value range, we filled in the ISIC code using the information provided by the name of the main product (*d1a1x*). If no information on the main product was available we used the screener sector to assign the 2-digit ISIC code. This manual filling process was applied for 46 observations (35 in 2005 and 1 in 2015). When all sector codes were assigned, we grouped

[29](1) Food & Beverage; (2) Textiles; (3) Apparel; (4) Leather products; (5) Wood & wood product, including furniture; (6) Paper; (7) Chemical & Chemical products; (8) Rubber & plastic products; (9) Non-metallic mineral products; (10) Basic metals; (11) Metal products; (12) Machinery, and equipment; (13) Electrical machinery; (14) Electronics; (18) Construction materials; (19) Vehicles, and other transport equipment, and (20) Other.

[30]The codes for manufacturing firms (Section D) are: (2) Other manufacturing; (15) Food; (16) Tobacco; (17) Textiles; (18) Garments; (19) Leather; (20) Wood; (21) Paper; (22) Publishing, printing, and Recorded media; Refined petroleum product; (23) Refined petroleum product; (24) Chemicals; (25) Plastics & rubber; (26) Non metallic mineral products; (27) Basic metals); (28) Fabricated metal products; (29) Machinery, and equipment; (31) Electronics; (33) Precision instruments; Transport machines (34); Furniture (36), and Recycling (37). The service sectors included in the Surveys are: (45) Construction (section F); (50) Services of motor vehicles; (51) Wholesale; (52) Retail; (55) Hotel, and restaurant (section H);, and (60) Transport (section I); (72) IT;, and other .

2-digit ISIC code into sectors as shown in Table 2.A2.

**[Table 2.A2 about here]**

#### 2.A.1.3 Firm Size

There is no variable that explicitly classifies firm size in the 2005 Survey. In the 2015 Survey firms are labelled as small (5-19 employees), medium (20-99 employees) or large (100, and above employees). However, this is based on the screener questionnaires, which may contain inaccurate information. Hence, we followed the manuals and reclassify firm size using the employment data gathered in the face-to-face interviews. Ideally, we would have relied on a combination of data on the number of permanent workers (*l1*), number of temporary workers (*l6*), and the average length of temporary employments (*l8*) to define the dimensions of firms. However, a large number of firms (especially in the 2005 Survey) did not provide their temporary employment data. To avoid the serious loss of information, we use the permanent employment numbers to put firms into four categories: small (<20), medium (20-99), large (100-299), and very large (300, and above). The small number of firms that did not provide this information are excluded from our analysis.

#### 2.A.1.4 Age

We calculate firm age based on a question when firms started their business. No assumption was made on missing values

#### 2.A.1.5 Ownership

We are interested in the share of the state and foreign owned firms. Two dummies were generated corresponding to an ownership that exceeds two thresholds 50% or 10%, which reflect different levels of state/ foreign influence on firm performance. The former threshold captures a majority ownership. According to Vietnam' Enterprise Law 2005 and 2014, the holder of 10% shares have some special rights including the right to nominate candidates to the Management Board and the Control Board.

#### 2.A.1.6 Legal Status

Based on the legal status variable, we generated a dummy for publicly traded companies. We also include a dummy for companies with traded shares among share-holding companies. We drop a negligible number of firms whose legal status is missing.

#### 2.A.1.7 Credit

We use questions on whether a firm has access to loan/credit from a financial institution to generate a binary variable for access to credit. No assumptions were made on missing values.

#### 2.A.1.8 Exporters

All surveys contain information about the exporting activities of firms. We assume that firms with missing values in the variables for the percentage of sales made up by indirect or/and direct exports (*d3b*, and *d3c*) are not involved in either/both activities (zero percent). Hence, we define a dummy variable for exporters as those that have a combination of both direct, and indirect exports value that account for at least 5% of their revenues.

### 2.A.2 Power Supply Provision

In each survey there are a number of variables that relate to the quality of power supply. The first is a binary variable (*c6*), which reveals whether firms suffered from any power outages over the last fiscal year. If the answer is yes, questions are then asked about the average number of power outages per month (*c7*), the typical length of an outage (*c8a*), estimated losses as a percentage of total sales due to power interruption (*c9a*), and the extent on a five level scale in which electricity is an obstacle to the operation of firms (*c30a*). Power outage duration was lower bounded at 1 hour in the 2005 Survey and 1 minute in the 2015 Survey.[31] As some firms report unreasonably high values for their power outage measurements, we put a limit of 20 (occurrences/month) on the outage numbers, and 96 (hours/occurrence). Any observation that exceeds these thresholds is replaced by these thresholds. Only 5/1,149 observations in Survey 2005, and 2/960 observations in Survey 2015 were subject to the replacement. The most extreme values of self-reported outage number for Survey 2005, and 2015 are 60, and 20 hours/occurrence respectively. The most extreme values of self-reported outage duration for Survey 2005, and 2015 are 400, and 480 hours/occurrence respectively. If we just use the raw data to calculate the volume of outages, there are three values that exceed 960 hours/month, roughly equivalent to 32 hours/day. We use the power outage frequency variable (the average number of power outages per month - *c7*), and the power outage intensity variable (typical

[31]There is a variable for minutes to add to the average power outage duration in hours (*_2015_c8* ), but this exists in the 2015 Survey only.

duration of an outage - *c8a*) as proxies for power (un)reliability.[32] The outage volume variable was computed as the product of these variable (after limits were imposed).

A typical mitigation measure of firms against the unreliability of power supply is the use of generators. There are two variables that proved useful: a binary variable for the equipment or share of generator(s) (variable *c10*), and the percentages of electricity generated from the generator(s) owned/shared by firms (variable *c11*). These variables are available for all firms in the 2005 Survey but not every firm in the 2015 Survey. Only firms that were interviewed by the Manufacturing Questionnaire in this year were asked these questions while other firms (in service sectors) interviewed by the Core Questionnaire or Retail Questionnaire were not.

### 2.A.3 TFPR Estimate

Since the concept of 'technical change' proposed by Solow (1957), productivity analysis has become an important tool to examine the economic performance in the sense of how efficiently resources are used by an aggregated economy or its agents. Specifically, firm data are used to estimate a production function, and its residual, measured total factor productivity (TFP), can be used to study policy impacts on firm performance (Van Beveren, 2012). OLS estimates of TFP, are known to be biased due to the simultaneity issues (Marschak and Andrews, 1944). The unobserved productivity shocks that firms already take into account when deciding the level of inputs, such as managerial ability, expected machine breakdown, expected defection rate, and expected rainfall pose identification challenges for OLS estimation (Ackerberg *et al.*, 2015). Consequently, positive shocks may lead to overestimation of input usage (De Loecker, 2011).

[32]For the special case of the 2015 Survey, we converted the variable *_2015_c8* from minutes to hours before added to *c8a* to compute the outage intensity variable)

The estimates of labour are downward biased in a two-factor setup where quasi-fixed capital, and flexible labour are positively correlated (Levinsohn and Petrin, 2003). Another source of endogeneity associated with panel data, where firms exit, and entry are dependent on their productivity, is attrition or selection bias. (Ackerberg *et al.*, 2007). This kind of endogeneity underestimates capital input, and overestimates TFP (Van Beveren, 2012).

There have been numerous methods designed to address the endogeneity issues. Fixed effects estimator are widely used to account for time-invariant firm specific characteristics that could correct both simultaneous bias, and selection bias (Pavcnik, 2002; Levinsohn and Petrin, 2003). However the validity of this estimator requires the strict exogeneity of the inputs conditional on firm characteristics (Wooldridge, 2009). Another solution is seeking a valid instrument, and relying on either an IV or GMM estimator. Some sources of instruments are price shocks of inputs, and outputs if the market is perfectly competitive, weather shocks, exogenous shocks from input markets, and dynamics of inputs (Ackerberg *et al.*, 2007; Van Beveren, 2012). Yet the validity of IVs are subject to debate. Olley and Pakes (1996) propose a semi-parametric estimator that uses investment decision as a proxy for the unobserved productivity shocks. The survival problem is also incorporated to account for selection bias that may arise in an unbalanced panel dataset. Alternatively, Levinsohn and Petrin (2003) use intermediate inputs rather than investment, which is susceptible to efficiency losses due to observations with zero value, as a proxy. However, such an estimate does not address selection bias. Some later estimation improvements include those proposed by Ackerberg *et al.* (2007); Wooldridge (2009); Katayama *et al.* (2009); De Loecker (2011).

In this study, as we work with cross-sectional data with a limited lags, there is a limited ability to apply the above methods. Hence, we decided to follow EAU-WB (2017), which uses two versions of the Cobb-Douglas production function to estimate TFP for each sector group, and addresses the endogeneity problem by adding dummies proxied for spatially-variant factors, and time-variant factors that is not observed . The first (the YKL model) assumes firms using two factors, namely capital ($K$), and labor ($L$), to generate output (Y). The second (the YKML model) adds materials (M) to the production function. The corresponding parameters $\alpha_K, \alpha_L, \alpha_M$ are factor intensities.

$$Y = A.K^{\alpha_K}.L^{\alpha_L} \text{ (YKL model)}$$

$$Y = A.K^{\alpha_K}.L^{\alpha_L}.M^{\alpha_M} \text{ (YKLM model)}$$

In our approach the estimation is based on a log-linear regression for each sector (indexed by $g$), including province fixed effects ($\beta_p$), and year fixed effects ($\gamma_y$), where $p$, and $y$ are, respectively, subscripts for provinces in which firms are located, and the year of the survey. Manufacturing firms are allocated to 11 sector groups (to ensure a reasonable sample size), including Food, beverages & tobacco (ISIC code 15, 16); Textiles (17); Garments (18); Leather products (19); Wooden products & furniture (20, 36); Paper, printing & publishing (21, 22); Refined petroleum products, chemicals, plastic & rubber (23 - 25); Non-metallic mineral products (26); Basic metal & Fabricated metal products (27, 28); Machinery, office, electronics & precision instruments (29 - 33), and Transport machines (34). Estimations were applied for manufacturing firms within our sample, excluding sectors that had too few observations (i.e., Mining & quarrying, and Recycling).

$$ln(Y_{gpy}) = \alpha_0 + \alpha_K.ln(K_{gpy}) + \alpha_L.ln(L_{gpy}) + \beta_p + \gamma_y + u_{gpy} \text{ (YKL model)}$$

$$ln(Y_{gpy}) = \alpha_0 + \alpha_K.ln(K_{gpy}) + \alpha_L.ln(L_{gpy}) + \alpha_M.ln(M_{gpy}) + \beta_p + \gamma_y + u_{gpy} \text{ (YKLM model)}$$

All variables are observed in monetary terms rather than physical ones: revenue (Y); replacement value of machinery, vehicles, and equipment (K); labor cost (L);, and materials cost (M). Hence, we do not explicitly estimate TFP, but its revenue-based version, TFPR (Total factor product revenue ) with the assumption of perfect market as follows:

$$ln(\widehat{TFPR}_{gpy}) = \hat{\alpha}_0 + \hat{\beta}_p + \hat{\gamma}_y + \hat{u}_{gpy}$$

From the two models (YKL, and YKLM), we obtain two sets of estimates of TFPR for manufacturing firms. The results of our production function are shown in Table 2.A3, and 2.A4. The YKLM model predicts total sales better than YKL (higher $\bar{R}^2$) but with a greater loss of observations due to missing values for material input costs. Our results also show heterogeneity in productivity across provinces, and across years. In addition, these two tables present a simple linear hypothesis test of constant returns to scale (CRS) where the null hypothesis is that the sum of total sales factor intensities in the production function equals 1.[33] The F-statistic in the last rows of these tables state that we cannot reject the CRS hypotheses at the given significant levels in almost every sector group. The exceptions are Food, beverages  tobacco, and Machinery, office, electronics & precision instruments in the YKLM model, whose sample rejects the null hypotheses at 10%. The estimates of coefficients suggest that these sector groups have decreasing returns to scale, and increasing returns to scale respectively.

[Table 2.A3 and 2.A4 about here]

[33]The null hypothesis for the YKL model is $\alpha_K + \alpha_L = 1$, and for the YKLM model is $\alpha_K + \alpha_L + \alpha_M = 1$

## 2.B Appendix B: Province-level Data Supplements

### 2.B.1 Provincial Economic Conditions

Variables for economic conditions at the province level were derived from gross output value of industry, and measures for provincial year-to-year industrial product (IP) growth. All data are extracted from *'Statistical Yearbooks of Vietnam'* by Vietnam's General Statistics Office (GSO).[34] Before 2010, the official measure for IP growth at the province level was the Index of industrial output value at constant 1994 prices. From 2010 on-wards, it was replaced by a more precise measure with a different methodology, namely the index of industrial production (IIP) with the base prices in 2010. As gross output value of industry by province is not available for the year 2014, we calculate an alternative, multiplying the gross output value of industry by province at current price in 2010 by a series of IIP from 2011 to 2014. This roughly reflects the gross output value of industry by province in 2014 at 2010 prices. We explicitly use two control variables. First, we compute the province IP share calculated as the ratio between the gross output industry at current prices or at 2010 prices of each province, and the whole country in each year. Second, we explicitly use the province IP index as a measure of IP growth at the province level.

### 2.B.2 Cooling Degrees

To compute cooling degree at the province level, we use gridded temperature data from the NCEP-DOE Renanlysis 2 provided by the NOAA/OAR/ESRL PSD. It is among a small number

[34] Accessible at http://www.gso.gov.vn/Default_en.aspx?tabid=515. Gross output value of industry comprises of the value of industrial products, and industrial services presented at either current prices or constant prices.

of datasets that provide global daily weather data for the entire year 2014 (and beyond). We downloaded daily forecast of Air temperature at 2m for a bounding box covering the entire Vietnam from http://www.esrl.noaa.gov/psd/ in netCDF format then read, and cleaned data with MatLAB.[35]

While covering a long course of updated, and consistent weather data, one disadvantage of the dataset is the low resolution ($2.5^0$x2.5), which is not good at capturing spatial variations in weather factors across provinces. Hence we need to use a spatial interpolation technique to dis-aggregate the data. There are a wide range of techniques, which can be generally put under 3 categories: non-geostatistical interpolators, geostatistical interpolators, and combined methods (see Li and Heap (2008) for a comprehensive comparison). We use a combined method, the "Gradient plus Inverse Distance Squared" (GIDS) method (proposed by Nalder and Wein (1998)) to do this task as it is able to account for a wide range of factors in large scale region with complex terrains (Stahl *et al.*, 2006). The method combines the advantages of multiple linear regression (MLR), and Inverse Distance Squared (IDS).

In the first step, we regress the temperature at daily time steps on a set of regressors including longitude ($Lon$), latitude ($Lat$), altitude ($Alt$), and distance to the sea ($Sea$), assuming that the temperature at each point ($i$) on day ($t$) is determined by its location, and topography characteristics.[36] To take into account the seasonality, regressions for two panels (Year 2004,

[35]The bounding box is 6-$26^0$N, and 100-$112^0$E, containing 66 nodes (stations. NetCDF (Network Common Data Form), hosted by the Unidata program at the University Corporation for Atmospheric Research (UCAR), is a set of software libraries, and self-describing, machine-independent data formats that support the creation, access, and sharing of array-oriented scientific data. See https://www.unidata.ucar.edu/software/netcdf/docs/faq.html#whatisit for more details.The original data have been packed into short integers for optimal storage. We unpacked the data by computing $unpacked\_value = add\_offset + packed\_value \times scale\_factor$ with $add\_offset = 0.01$, and $scale\_factor = 447.65$ as provided by the metadata.

[36]$Lat$, $Lon$, $Alt$ are the variables most frequently used in GIDS. We include $Sea$ to the model as Vietnam has a long coastal line hence its climate is affected by the sea. The impact of the sea on local climate is proposed in Maureen and Jean (2000).

and 2014) are run separately by month $m = 1, 2, ..., 12$.

$$Tit = \alpha_m + \beta_m Lon_{it} + \gamma_m Lat_{it} + \delta_m Alt_{it} + \phi_m Sea_{it} + \varepsilon_{it} \tag{B1}$$

The results of the MLR are shown in Table 2.B1. All regressors appear to be significant predictors of temperature. Overall, temperature is lower in the North (high latitude) across all years, while the sign of variation across longitude is subject to seasonality. Temperature falls in more elevated regions, with an estimated lapse rate of 1.07 - 1.99 $^0C/km$ in 2004, and 0.88-1.85 $^0C/km$ in 2014. These values are lower than those proposed in the literature ($6 - 6.5^0C$), probably due to the multicollinearity with other regressors (for example, mountainous, and hilly terrains are concentrated in the Northern and Western parts of the countries). In addition, the sea also has a significant impact on climate patterns, lowering the temperature with a magnitude that varies across the month. The predictability of the regression is stronger between June- January ($R^2$ exceeding 80%). In other months, the $R^2$ is lower but never falls below 65%. The goodness-of-fit of the model is much lower (56.1% in 2004, and 49.7% in 2014) when we pool all observations across different months and captures the strong seasonality of the climate pattern. As a result we run separate regressions for each month.

After obtaining parameters of the MLR, we predict the temperature of province $j$ using temperatures at the 5 nearest stations based on IDW method.

$$\begin{aligned} T_{jt} = {} & \Big(\sum_{k=1}^{5} \frac{1}{d_{jk}^2}\Big)^{-1} \\ & \times \sum_{k=1}^{5} \Big[T_{kt} + \hat{\beta}_m(Lon_{jt} - Lon_{kt}) + \hat{\gamma}_m(Lat_{jt} - Lat_{kt}) + \hat{\delta}_m(Alt_{jt} - Alt_{kt}) + \hat{\phi}_m(Sea_{jt} - Sea_{kt})\Big]\frac{1}{d_{jk}^2} \end{aligned} \tag{B2}$$

where $d_{jk}$ is the geodesic distance between the centroid of province $j$, and station $k$. $T_{kt}$ is the temperature observed in station $k$ at time $t$, which is located at $Lon_{kt}$, $Lat_{kt}$, $Alt_{kt}$, and within a distance of $Sea_{kt}$ to the sea. $T_{jt}$ is the interpolated temperature of province $j$ at time $t$, whose centroid is located at $Lon_{jt}$, $Lat_{jt}$, and within a distance of $Sea_{jt}$ to the sea. $Alt_{jt}$ is calculated as the average elevation of the target province. $\hat{\beta}_m$, $\hat{\gamma}_m$, $\hat{\delta}_m$, and $\hat{\phi}_m$ are parameters estimated in Equation B1. The method is essentially equivalent to assigning $T_{jt} = \hat{T}_{jt} + \bar{\hat{\varepsilon}}_{jt}$, where $\hat{T}_{jt}$ is the predicted temperature for province $j$ at time $t$ by regression B1, and $\bar{\hat{\varepsilon}}_{jt}$ is the weighted average of the residuals at 5 nearest stations.[37] Intuitively, $\hat{T}_{jt}$ accounts for predetermined factors in the model B1 while $\varepsilon_{jt}$ accounts for other unobserved factors outside the model. The predicted values are in Celsius degrees.[38] We converted them into Fahrenheit, and then calculated the cooling degree $C_{it} = max\{0; T_{it} - 65\}$, which was then aggregated at the year level.

**[Table 2.B1 about here]**

### 2.B.3 Rainfall Shocks

For rainfall data we use 'Terrestrial Air Temperature, and Precipitation: Monthly Climatologies' (version 4.1) by the Daleware University (Matsuura and Willmott, 2009). Previous studies have used this data to construct rainfall shock variables (Kaur, 2014; Sarsons, 2015; Allcott *et al.*, 2016). We obtained monthly data for 40 years (1975-2014) for 459 stations at 0.5× 0.5 degree resolution.[39] Although this resolution is finer than the temperature data but still not sufficient to capture variation across provinces. To interpolate rainfall data, we use a similar GIDS method

[37]The mean(maximum) distance in km from province centroid to the 1st, 2nd, 3rd, 4th, and 5th nearest station are 75(124); 144(185); 191(213); 213(235); 250(294).

[38]The raw data were recorded in Kelvin.

[39]Restricted by the bounding box 8-24$^0$N, and $100 - 112^0$E.

as described above, where temperature is replaced by rainfall. There are several differences. First, the rainfall variable is log transformed to reduce the skewness of the dependent variable, and to ensure that the predicted values of rainfall are non-negative. Such a transformation is necessary as the normality of all monthly rainfall series are rejected by either Shapiro –Wilk or Shapiro –Francia test at the 1% level. We consider two regression specifications: double log regression, and semi log regression as illustrated in Table 2.B2. All predetermined factors (coordinates, altitude, and distance to the sea) appear with significant coefficients, however the sign, and magnitude of these variables change across months, reflecting the seasonal patterns. The predictability of the regressions are much lower than those for temperature in Table 2.B1, so the IDW component is probably more important in the interpolation method. We decided to use the double log regression as it is easier to interpret the results, and the performance of the model across months is more stable.[40] After obtaining the parameters, we apply the IDW method, similar to Equation B2, using 7 nearest stations to predict the log of rainfall at the centroid of the province (assigned average province altitude). [41]

**[Table 2.B2 about here]**

The Standardised Precipitation Index (SPI) for each province is constructed as follows. First we aggregate by 12 month moving windows the 40 years for each province. Second, we fit the data to a Gamma distribution whose cumulative probability is determined by 2 parameters $\alpha, \beta > 0$:

$$G(x) = \int_0^\infty \frac{1}{\beta^\alpha \Gamma(\alpha)} r^{\alpha-1} e^{-r/\beta} \tag{B3}$$

[40] For example, rainfall in January respectively increases by 2.06%, 9.66%, 0.62%, and 0.09% in response to 1% increase in latitude, longitude, altitude, and proximity to the sea. The $R^2$ varies between 0.033, and 0.209 in the double log specification, and between 0.020, and 0.227 in the semi log specification.

[41] The mean(maximum) distance in km from province centroid to the 1st, 2nd, 3rd, 4th, 5th, 6th, and 7th nearest station are 20(39); 41 (59); 52(73); 62(89); 74(98); 78(99) 87(114).

where $r > 0$ is the accumulated precipitation (rainfall in our case), and $\Gamma(\alpha)$ is the Gamma function defined by:

$$\Gamma(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy \tag{B4}$$

The cumulative distribution function $G(x)$ is then transformed into a normal distribution with mean $r^*$, and standard deviation $\sigma$.[42] Finally, the SPI is computed as:

$$SPI = \frac{r - r^*}{\sigma} \tag{B5}$$

SPI for province $j$ at time $t$ is calculated as the SPI of province $j$ in the window that contains all months of year $t$. The spatial distribution of cooling degree and SPI is shown in Figure 2.A.1.

**[Figure 2.A.1 about here]**

### 2.B.4 Grid-based Distance to Hydropower Plants

The electricity lines dataset includes 116 polylines, of which 16 are 500-kV grid, and 100 are 220-kV grid. In terms of status, 48 are labelled 'existing', and 68 are lablled 'planned'. Supplementary documents suggest that the 'existing' lines are those on-line by January 2005, and the 'planned' are those proposed to be built by 2010 or 2020. Unfortunately, other details on the dynamic of the system are unavailable (the operation year of each line). For simplicity, we use all grids (both those labelled 'existing', and 'planned') for both WBES while allowing the number of hydropower sources to increase over time. A justification for the use of 'planned'

[42] If $r$ contain zero values, the cumulative prbability should be expressed as $H(x) = q + (1 - q)G(x)$, where $q$ is the probability to have zero rainfall. However, zero values do not present in our accumulate rainfall series at 12-month windows.

transmission lines even in the earlier WBES is that although they certainly were not constructed in 2004, there could have been lower-voltage lines that had been operating in that location (i.e., 22 kV up to 110 kV), and were later upgraded to 220 kV or 500 kV as 'planned' lines in this dataset.

The construction of the grid-based distance between each pair of hydropower plants, and a province centre is as follows. First, we assigned the plant, and the province the nearest point on the grid, then compute the grid-based distance as the sum of the geodesic distances between the plant/ province, and their assigned nearest points, and the length of the shortest route that connects the two assigned points through the transmission network. Technically, we used a number of different ArcGIS tools to aid our computation. First, the assignment of the nearest points, and the calculation of their distances to either the power source or the electric consumption center was executed by the *Near* tool of the *Analysis* toolbox. The *Integrate* tool of the *Data Management* toolbox was applied to strengthen the connectivity of the poly-lines within the dataset, which was then transformed into a network dataset by *Network Analyst* extension. Finally, the distance between the assigned grid points of all pair of given hydropower plants, and WBES surveyed provinces were computed by the *Origin-Destination cost matrix analysis* tool, and visualised for validation by the *Route analysis* tool.

The visual validation detected a number of pairs that are linked by unreasonably long routes compared with their Geodesic distances. A reason is the absence of low-voltage lines (under 220 kV) in our grid dataset, which help connect those in close proximity. This requested for some adjustments. As a results, We computed the ratios between the grid-based distances, and Geodesic distances, and then define outliers as those that are more than one standard error deviation from the sample mean. We then adjust the grid-based distances of the outliers by the product of their geodesic distances, and the mean ratio of the sample. Figure 2.B.1 provides a comparison on the grid-based distances, and the Geodesic distances before, and after the adjustment.

[**Figure 2.B.1 about here**]

## 2.C Appendix C: Robustness Checks

### 2.C.1 Alternative Instrumental Variables

Table 2.C1 presents a number of robustness checks, where alternative IVs are used, while the other control variables are kept unchanged. The first six columns are for Survey 2005, and the others are for Survey 2015. For simplicity, we only use volume to measure the degree of power outages in these robustness checks.

**[Table 2.C1 about here]**

In Columns (2), and (8) the IVs were constructed from geodesic distance rather than grid-based distance in baseline. In general there is just little difference in the estimates of coefficients in regressions using these IVs. If the grid map had been missing, regressions based on IVs derived from geodesic distances would have still been useful. The IVs that are constructed directly from the real generation of hydropower plants (Column (3), and (9)) appear to be much weaker than the baseline. The coefficients of revenue in these columns tend to be larger than those in the baseline, and even positive (Column 3), suggesting the problem with exogeneity of the IV constructed by actual generation. Due to the operation of large reservoirs, the real generation series incorporates a large part of power demand fluctuation, and loses a certain amount of exogenous shocks from weather factors, and just adds limited information to the reduced equations once demand variations are strictly controlled for (i.e., cooling degree, IP index, IP share). This highlights the importance of the use of the hydrologically-based generation model in this study.

In Columns (4), and (10) we construct the IVs from the generation model that excludes the installed capacity of upstream dams. Consequently, the IV for Survey 2015 become much weaker as cascades of hydropower play an important role in the power supply of the country. Taking the synergies of dams into account strengthens the IVs in our national-scaled study with a single-grid context. In column (5) we construct the IVs for Survey 2005 that strictly replicate those of Survey 2015, based on hydrologcially-predicted generation in the first 7 months rather than the entire year. The IVs seem to be a little bit weaker than the baseline, and tend to report a larger magnitude of the reduction in performance. However, such a change does not drive the reduction in output. In Columns (6), and (12) we include time dummies to the generation prediction equation prior to the construction of the IVs. These alternative IVs seem to be weaker than the baseline. The 2SLS estimates using different alternative IVs are consistent with our baseline results. The alternative IVs confirm the finding that power deficiency is more important in Survey 2015 rather than Survey 2005. The alternative IVs also find a reduction in TFPR estimated by the YKLM model for the 2005 Survey, and all of them report a significant reduction in the YKL model results for the 2015 Survey. Almost every set of IVs reports an increase in generator use, and a reduction in energy, in general, and grid electricity, in particular, in response to more severe power outages in both years. A *t-test* in column (9), and (10) report a significant reduction in materials, and labour inputs due to power disruptions for Survey 2015 while the AR$\chi^2$ test report these results in the majority of columns.

### 2.C.2 Firm Heterogeneity

Table 2.C2 shows the results of the baseline 2SLS regressions for different sub-samples: manufacturing firms, firms with generators, firms without generators, electricity-intensive firms, non-electricity-intensive firms, exporters, and non-exporters.[43] Again, we use outage volume to measure the unreliability of power supply. According to the first stage results, the IV is relevant for all sub-samples in both year (at the 5% level, and even the 1% level for many sub-samples). In panel A (Survey 2005) the signs for the impacts of power outages on sales are all negative, except for the subsample of generator-owners, and non-exporters. However, all of the impacts are insignificant as reported by the *t-tests*. The AR $\chi^2$ tests reports a significant sale loss for the non-exporter subsample only where the associated coefficient is -0.86. For panel B (Survey 2015) all sub-samples excluding non-electricity-intensive show a significant reduction in revenues where outage volume is high. In terms of magnitude, the coefficients vary between -0.16 to -1.48. In both years the magnitude of sale loss due to power outages slightly increases when services firms are excluded.

**[Table 2.C2 about here]**

[43] Electricity-intensive firms are labelled as those in the industries whose electricity share in revenue exceeds the median of the sample.

### 2.C.3 Deviations in the Survey Designs

In this subsection we review some differences in the design, and implementation of two surveys, and test whether they drive the difference in the magnitude, and significance of power outage impacts. First, Survey 2015 reports the duration of power outages with higher accuracy as it includes a variable for minutes in addition to a variable of duration in hour (*_2015_c8*).[44] When we round up duration in Survey 2015 according to the style in Survey 2005, there are only discernible changes (at the second decimal place) in the estimates of the coefficient, and their standard errors, and no change in the significance of power outage impacts.

Second, while all firms in Survey 2005 reports the data for the entire 2004 fiscal year, a number of firms (293 firms ~ 29.5%) do not report for the entire 2014 fiscal year.[45] In the baseline regressions we retain all observations, and assume that other control variables fully account for the difference between these firms, and those that report the entire 2014 fiscal year. For robustness we include a dummy to indicate the group of these special observations in Column (2) of Table 2.C3. The coefficient of output loss is -0.55, a little bit smaller in magnitude than the baseline (-0.73), however still larger than the estimate for Survey 2005. A *t-test* can not reject the null that the newly added dummy is an insignificant predictor of the revenue given the rich control variable set. This may help justify our use of the baseline specification.

**[Table 2.C3 about here]**

Third, in columns (3) - (5), we take into account the weights, which is available for Survey

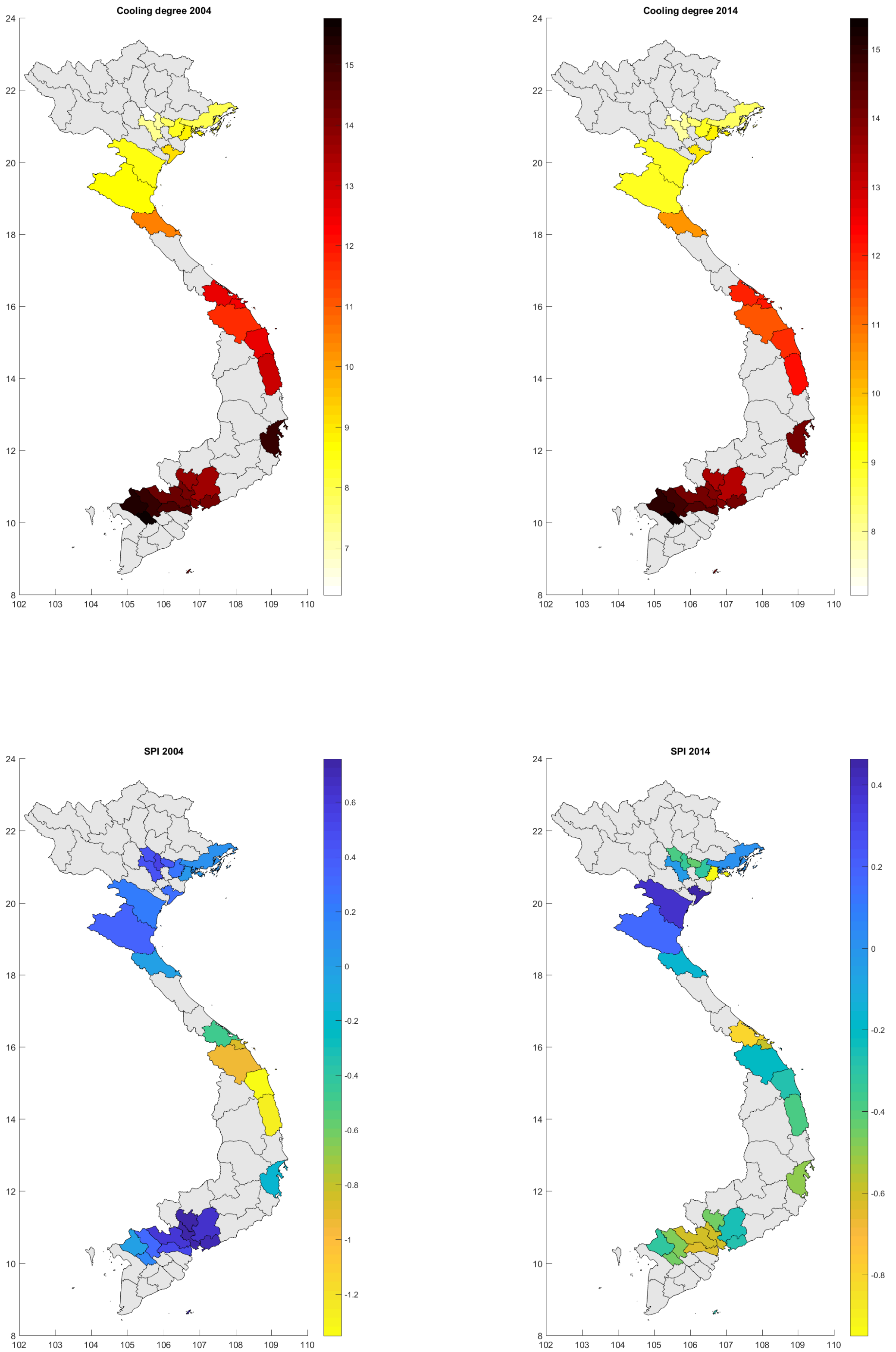
[44] That means firms in Survey 2015 report the duration up to a minute (for example 2 hour, and 18 minutes) while firms in Survey 2005 only report up to a half of hour (for example .5 hours).

[45] It could happen as some interviews occur too early for firms to prepare data for the whole fiscal year, and hence report the data of the latest 12 months instead.

2015 but not 2005. Three weights are provided in the dataset, computed based on stratum, and three different assumptions on the eligible firms (strict, median, and weak).[46] As can be seen, the three weights provide quite similar coefficients for all dependent variables. These estimates confirm the evidence provided by the baseline that firms with a disadvantage in power provision generate less revenue, self-generate more, and use less electricity from the grid. As the stratification in the WBES is based on 3 conditioning variables (sector, size, province), we prefer the unweighted estimator. As long as the stratification is based on the independent variables, the unweighted estimator is shown to be consistent, and the validity of the usual asymptotic variance matrix estimator remains (Wooldridge, 2010, pg863). Furthermore, under generalised conditional information matrix equality, the weighted estimator is less efficient than the unweighted estimator (Wooldridge, 1999, 2001).

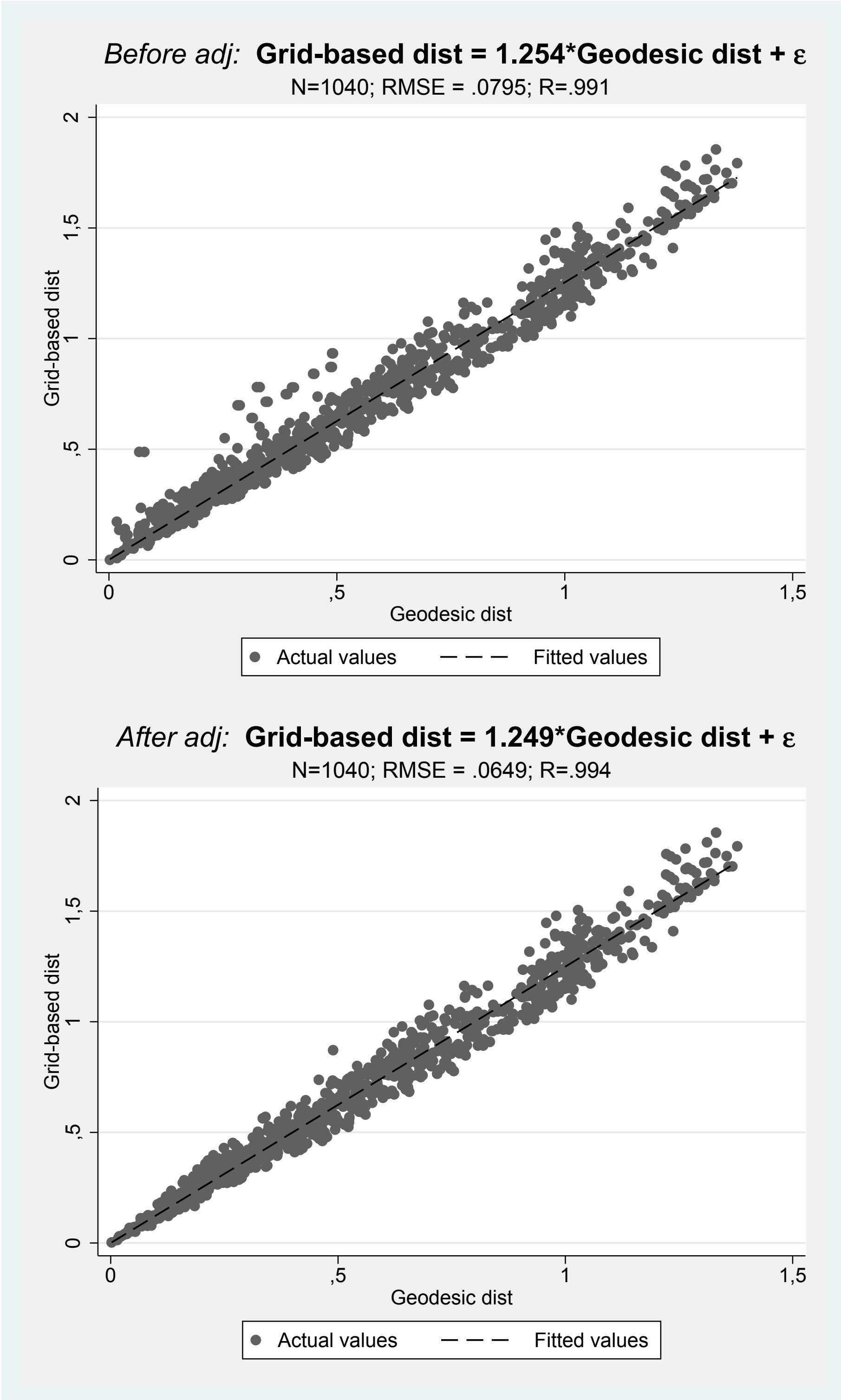
[46]Strict assumption: eligible establishments are only those for which it was possible to directly determine eligibility. Median assumption: eligible establishments are those for which it was possible to directly determine eligibility, and those that rejected the screener questionnaire or an answering machine or fax was the only response. Weak assumption: in addition to the establishments included in points a, and b, all establishments for which it was not possible to contact or that refused the screening questionnaire are assumed eligible.

**Figure 2.A.1: Cooling degree and Standardised Precipitation Index (SPI)**




*Source:* Cooling degree and SPI are calculated for provinces in either waves of WBES 2005/2015 from the gridded weather data provided by NOAA/OAR/ESRL (temperature) and the University of Delaware (rainfall). The administrative GIS map (before the extension of Hanoi) in 2005 was used. See text and Appendix 2.A.1 for the weighted method used to calculate the variables for firms in expanded Hanoi for Survey 2015.

**Figure 2.B.1: Grid-based distances vs Geodetic distances comparison**




*Note:* The graph compares the Grid-based distances and Geodetic distances between Vietnam's provinces surveyed by the WBES 2005/2015 and hydropower dams used to construct the IV. See text for more definitions and methodology of distance construction. Adjustments were applied on the outliers, whose ratio between the grid-based distance and geodetic distance more than one standard error deviates from the sample mean. The grid-based distances of the outliers were replaced by the product of the corresponding geodetic distances and the sample mean of the ratio.

**Table 2.A1: Province, and region statistics by year**

| Province | Region | 2005 | | 2015 | |
|---|---|---|---|---|---|
| | | *Frq* | *Per* | *Frq* | *Per* |
| Ha Noi (mun. cap.) | Red River Delta | 139 | 12.09% | 174 | 17.47% |
| Hai Phong (mun.) | Red River Delta | 80 | 6.96% | 72 | 7.23% |
| Ha Tay (before merge) | Red River Delta | 44 | 3.83% | 0 | 0.00% |
| Bac Ninh | Red River Delta | 22 | 1.91% | 9 | 0.90% |
| Hai Duong | Red River Delta | 19 | 1.65% | 30 | 3.01% |
| Nam Dinh | Red River Delta | 41 | 3.57% | 11 | 1.10% |
| Quang Ninh | Red River Delta | 0 | 0.00% | 8 | 0.80% |
| ***Total region*** | ***Red River Delta*** | ***345*** | ***30.00%*** | ***304*** | ***30.52%*** |
| Thanh Hoa | North Central | 64 | 5.57% | 47 | 4.72% |
| Nghe An | North Central | 39 | 3.39% | 48 | 4.82% |
| Ha Tinh | North Central | 27 | 2.35% | 0 | 0.00% |
| Thua Thien Hue | North Central | 20 | 1.74% | 6 | 0.60% |
| ***Total region*** | ***North Central*** | ***150*** | ***13.04%*** | ***101*** | ***10.14%*** |
| Da Nang (mun.) | Coastal Central | 46 | 4.00% | 81 | 8.13% |
| Quang Nam | Coastal Central | 16 | 1.39% | 0 | 0.00% |
| Quang Ngai | Coastal Central | 9 | 0.78% | 0 | 0.00% |
| Binh Dinh | Coastal Central | 39 | 3.39% | 13 | 1.31% |
| Khanh Hoa | Coastal Central | 38 | 3.30% | 44 | 4.42% |
| ***Total region*** | ***Coastal Central*** | ***148*** | ***12.87%*** | ***138*** | ***13.86%*** |
| Ho Chi Minh (mun.) | South East | 242 | 21.04% | 191 | 19.18% |
| Binh Duong | South East | 77 | 6.70% | 30 | 3.01% |
| Dong Nai | South East | 61 | 5.30% | 83 | 8.33% |
| Ba Ria - Vung Tau | South East | 15 | 1.30% | 3 | 0.30% |
| ***Total region*** | ***South East*** | ***395*** | ***34.35%*** | ***307*** | ***30.82%*** |
| Long An | Mekong River Delta | 36 | 3.13% | 60 | 6.02% |
| Dong Thap | Mekong River Delta | 7 | 0.61% | 0 | 0.00% |
| An Giang | Mekong River Delta | 16 | 1.39% | 0 | 0.00% |
| Tien Giang | Mekong River Delta | 16 | 1.39% | 32 | 3.21% |
| Can Tho (mun.) | Mekong River Delta | 37 | 3.22% | 52 | 5.22% |
| ***Total region*** | ***Mekong River Delta*** | ***112*** | ***9.74%*** | ***144*** | ***14.46%*** |
| | ***Unidentified*** | ***0*** | ***0.00%*** | ***2*** | ***0.20%*** |
| | **Total sample** | **1150** | **100.00%** | **996** | **100.00%** |

*Source:* Author's extracted from the clean database. *Note:* mun. = municipalities; cap. = the capital

**Table 2.A2: Sector reclassification**

| Sector | ISIC code | 2005 | | 2015 | |
|---|---|---|---|---|---|
| | | *Freq* | *Percent* | *Freq* | *Percent* |
| Mining & quarrying | 10 - 14 | 7 | 0.61% | 0 | 0.00% |
| Food, beverages & tobacco | 15, 16 | 197 | 17.13% | 130 | 13.05% |
| Textiles | 17 | 46 | 4.00% | 24 | 2.41% |
| Garments | 18 | 110 | 9.57% | 140 | 14.06% |
| Leather | 19 | 41 | 3.57% | 14 | 1.41% |
| Wood | 20 | 88 | 7.65% | 21 | 2.11% |
| Paper | 21 | 70 | 6.09% | 8 | 0.80% |
| Publishing, printing & recorded media | 22 | 2 | 0.17% | 12 | 1.20% |
| Refined petroleum product & chemicals | 23, 24 | 72 | 6.26% | 19 | 1.91% |
| Plastics & rubber | 25 | 58 | 5.04% | 20 | 2.01% |
| Non-metallic mineral products | 26 | 126 | 10.96% | 131 | 13.15% |
| Basic metals | 27 | 36 | 3.13% | 14 | 1.41% |
| Fabricated metal products | 28 | 63 | 5.48% | 98 | 9.84% |
| Machinery | 29 | 66 | 5.74% | 35 | 3.51% |
| Office, electronics & precision instruments | 30-33 | 36 | 3.13% | 10 | 1.00% |
| Transport machines | 34, 35 | 57 | 4.96% | 3 | 0.30% |
| Furniture | 36 | 62 | 5.39% | 12 | 1.20% |
| Recycling | 37 | 0 | 0.00% | 3 | 0.30% |
| Construction (section F) | 45 | 9 | 0.78% | 75 | 7.53% |
| Motor vehicles services | 50 | 1 | 0.09% | 13 | 1.31% |
| Wholesale | 51 | 0 | 0.00% | 106 | 10.64% |
| Retail | 52 | 0 | 0.00% | 61 | 6.12% |
| Hotels and restaurants (section H) | 55 | 0 | 0.00% | 15 | 1.51% |
| Transport (section I) | 60 - 64 | 2 | 0.17% | 28 | 2.81% |
| IT | 72 | 0 | 0.00% | 4 | 0.40% |
| Other services | 85 | 1 | 0.09% | 0 | 0.00% |
| Unidentified | 99 | 0 | 0.00% | 0 | 0.00% |
| **Total** | | **1150** | **100.00%** | **996** | **100.00%** |

*Source:* Authors redefined sector of firms in the World Bank Panel dataset of Vietnam 2005-2009-2015 Enterprise Surveys based on the 2 first digits of the ISIC code of the main product in terms of revenue share.

## Table 2.A3: TFPR estimate using YKL model

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 | Group 9 | Group 10 | Group 11 |
| **Factor** | | | | | | | | | | | |
| Capital stock; log | 0.247*** | 0.166 | 0.477*** | 0.367* | 0.288*** | 0.119** | 0.123* | 0.209*** | 0.260*** | 0.274*** | 0.123* |
| | (0.0524) | (0.107) | (0.0576) | (0.197) | (0.0617) | (0.0460) | (0.0657) | (0.0521) | (0.0730) | (0.0526) | (0.0700) |
| Labor cost; log | 0.762*** | 0.803*** | 0.457*** | 0.514* | 0.653*** | 0.853*** | 0.855*** | 0.801*** | 0.724*** | 0.793*** | 0.935*** |
| | (0.0665) | (0.141) | (0.0741) | (0.275) | (0.104) | (0.0896) | (0.0810) | (0.0774) | (0.0802) | (0.0730) | (0.140) |
| **Province** | | | | | | | | | | | |
| Hai Phong (mun.) | 0.0865 | | -0.298 | -0.573 | 1.178* | -1.502*** | 0.0349 | 0.654 | 0.451 | -0.140 | -0.0268 |
| | (0.358) | | (0.387) | (1.252) | (0.605) | (0.363) | (0.285) | (0.623) | (0.408) | (0.244) | (0.477) |
| Ha Tay (before merge) | -0.556* | -1.253 | -0.123 | | 0.269 | -0.808** | | -0.290 | 0.834 | -1.350*** | 0.0388 |
| | (0.323) | (0.855) | (0.302) | | (0.358) | (0.315) | | (0.302) | (0.554) | (0.375) | (0.430) |
| Bac Ninh | | | 0.285 | -0.339 | 0.453 | -0.559* | | -0.000906 | 0.589** | -0.227 | |
| | | | (0.946) | (0.914) | (0.484) | (0.279) | | (0.488) | (0.258) | (0.208) | |

*cont.*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 | Group 9 | Group 10 | Group 11 |
| Hai Duong | 0.170 | -1.846*** | 0.144 | 0.155 | 0.301 | -0.297 | -1.426*** | 0.353 | 0.499 | -0.599** | |
| | (0.262) | (0.338) | (0.317) | (1.159) | (0.457) | (0.457) | (0.442) | (0.680) | (1.022) | (0.253) | |
| Nam Dinh | -0.194 | -0.932 | 0.164 | 0.361 | 0.432 | -0.271 | 0.235 | -0.360 | | -0.388 | -0.631 |
| | (0.569) | (0.698) | (0.626) | (0.781) | (0.365) | (0.239) | (0.552) | (0.314) | | (0.332) | (0.695) |
| Quang Ninh | | | | | 1.748*** | | | -0.177 | 0.0320 | | |
| | | | | | (0.283) | | | (0.288) | (0.266) | | |
| Thanh Hoa | 0.0613 | -0.0214 | 0.102 | | -0.126 | -0.686 | -0.827*** | -0.444 | 0.0744 | -0.156 | -0.445 |
| | (0.420) | (0.308) | (0.509) | | (0.325) | (0.760) | (0.276) | (0.286) | (0.391) | (0.273) | (0.448) |
| Nghe An | -0.527* | | -0.216 | 0.216 | 0.258 | -0.483* | 0.665 | -0.250 | -0.205 | 0.467* | |
| | (0.299) | | (0.400) | (0.771) | (0.265) | (0.287) | (0.591) | (0.291) | (0.697) | (0.279) | |
| Ha Tinh | 0.00359 | -0.722 | -0.527 | | 0.341 | 0.881*** | | -0.120 | -0.402 | -0.573*** | -0.534 |
| | (0.540) | (0.490) | (0.326) | | (0.451) | (0.233) | | (0.338) | (0.276) | (0.202) | (0.386) |
| Thua Thien Hue | -0.831*** | -1.545** | -0.610* | 1.110 | 0.347 | 1.418*** | -0.0818 | | -0.349 | -0.671 | -0.00179 |
| | (0.282) | (0.589) | (0.314) | (1.295) | (0.490) | (0.372) | (0.357) | | (0.326) | (0.462) | (0.362) |
| Da Nang (mun.) | 0.171 | -0.229 | 0.0333 | 0.603 | -0.150 | -0.942*** | 0.589 | -0.451 | 0.275 | 0.524 | -0.182 |
| | (0.438) | (0.752) | (0.359) | (1.254) | (0.356) | (0.273) | (0.524) | (0.332) | (0.321) | (0.592) | (0.410) |

*cont.*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 | Group 9 | Group 10 | Group 11 |
| Quang Nam | -0.405 | | -0.0910 | -1.396 | 0.316 | -0.723*** | -0.579 | -0.0691 | | | 0.794* |
| | (0.499) | | (0.378) | (0.896) | (0.387) | (0.198) | (0.932) | (0.471) | | | (0.393) |
| Quang Ngai | -0.956*** | | | | -0.566* | | 0.124 | -0.182 | | | -0.385 |
| | (0.241) | | | | (0.288) | | (0.360) | (0.557) | | | (0.469) |
| Binh Dinh | 0.255 | -3.013*** | 0.114 | | 0.598** | -0.745*** | -0.428 | -0.0135 | -0.296 | | |
| | (0.430) | (0.420) | (0.617) | | (0.295) | (0.216) | (0.305) | (0.612) | (0.399) | | |
| Khanh Hoa | 0.221 | 0.574* | 0.200 | | 0.463 | -0.905*** | -0.152 | | -0.403 | 0.259 | -0.362 |
| | (0.308) | (0.318) | (0.544) | | (0.541) | (0.237) | (0.328) | | (0.249) | (0.230) | (0.400) |
| Ho Chi Minh (mun.) | 0.320 | -0.472 | 0.567* | 0.601 | 0.0701 | -0.490* | 0.187 | -0.146 | 0.309 | -0.136 | 0.420 |
| | (0.296) | (0.432) | (0.306) | (1.264) | (0.281) | (0.264) | (0.280) | (0.420) | (0.324) | (0.231) | (0.515) |
| Binh Duong | 0.171 | -0.459 | -0.303 | 0.423 | 0.769** | -0.848 | 0.155 | -0.539** | 0.212 | -0.0998 | -0.0439 |
| | (0.716) | (0.425) | (0.398) | (0.978) | (0.364) | (0.515) | (0.520) | (0.265) | (0.581) | (0.458) | (0.540) |
| Dong Nai | 0.373 | -0.0166 | -0.154 | -0.286 | 0.469 | 0.228 | 0.382 | 0.333 | 0.857* | -0.118 | 0.395 |
| | (0.547) | (0.335) | (0.439) | (0.604) | (0.390) | (0.376) | (0.352) | (0.303) | (0.464) | (0.262) | (0.512) |
| Ba Ria - Vung Tau | 0.109 | | -0.666 | 0.0309 | | | | | 0.398 | | |
| | (0.317) | | (0.634) | (1.172) | | | | | (0.291) | | |

*cont.*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 | Group 9 | Group 10 | Group 11 |
| Long An | 0.106 | 0.197 | -0.112 | 1.186 | 0.101 | -0.698** | -0.00645 | -0.0830 | 0.485 | -0.0357 | |
| | (0.307) | (0.560) | (0.410) | (1.304) | (0.236) | (0.280) | (0.431) | (0.513) | (0.457) | (0.295) | |
| Dong Thap | 1.143 | | | | | | | | | | -1.747*** |
| | (1.353) | | | | | | | | | | (0.429) |
| An Giang | 0.852*** | | 0.102 | 0.931 | | | | | 0.240 | | |
| | (0.327) | | (0.332) | (1.361) | | | | | (0.268) | | |
| Tien Giang | -0.362 | -2.503*** | -0.127 | | | | -0.967** | -0.892*** | 1.945*** | | |
| | (0.416) | (0.385) | (0.393) | | | | (0.378) | (0.263) | (0.347) | | |
| Can Tho (mun.) | 1.232*** | | -0.151 | -0.0339 | | -0.521 | -0.196 | 0.263 | -0.241 | -0.705 | 0.762 |
| | (0.323) | | (0.311) | (1.103) | | (0.378) | (0.558) | (0.798) | (0.409) | (0.776) | (0.629) |
| **Survey** | | | | | | | | | | | |
| 2015 | -0.369** | 0.566 | 0.452** | 0.0578 | 0.428* | -1.222*** | -0.163 | 0.154 | -0.0320 | -0.256 | -0.917 |
| | (0.177) | (0.431) | (0.192) | (0.814) | (0.244) | (0.257) | (0.229) | (0.176) | (0.213) | (0.258) | (0.605) |
| Constant | 2.103*** | 2.900 | 2.253* | 3.256* | 2.606** | 3.399** | 2.726*** | 1.627 | 2.205** | 0.962 | 1.387 |
| | (0.807) | (2.196) | (1.196) | (1.646) | (1.298) | (1.348) | (0.990) | (0.993) | (0.991) | (0.829) | (2.148) |

*cont.*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 | Group 9 | Group 10 | Group 11 |
| Observations | 243 | 58 | 191 | 44 | 161 | 75 | 135 | 195 | 155 | 107 | 54 |
| R-squared | 0.785 | 0.799 | 0.751 | 0.787 | 0.720 | 0.875 | 0.801 | 0.748 | 0.693 | 0.880 | 0.867 |
| $\alpha_K + \alpha_L$ | 1.01 | 0.97 | 0.93 | 0.88 | 0.94 | 0.97 | 0.98 | 1.01 | 0.98 | 1.07 | 1.06 |
| CRS F-stat | 0.04 | 0.06 | 1.15 | 0.87 | 0.63 | 0.11 | 0.15 | 0.03 | 0.09 | 2.28 | 0.25 |

*Note:* Sector group definition: Group 1 = Food, beverages & tobacco (ISIC code 15,16); Group 2 = Textiles (17); Group 3 = Garments (18); Group 4 = Leather products (19); Group 5 = Wooden products & furniture (20, 36); Group 6 = Paper, printing & publishing (21 & 22); Group 7 = Refined petroleum products, chemicals, plastic & rubber (23 - 25); Group 8 = Non-metallic mineral products (26); Group 9 = Basic metal & Fabricated metal products (27 & 28); Group 10 = machinery, office, electronics & precision instruments (29 - 33); Group 11 = Transport machines (34).

The reference group for fixed effects is firms that are located in Hanoi (mun. cap.), and surveyed in 2005. The dependent variable is the log of revenues. Standard errors in parentheses. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table 2.A4: TFPR estimate using YKLM model**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 | Group 9 | Group 10 | Group 11 |
| **Factor** | | | | | | | | | | | |
| Capital stock; log | 0.0762*** | 0.0186 | 0.211*** | 0.0636 | 0.0437** | 0.0446 | 0.103* | 0.184*** | 0.0560 | 0.123*** | -0.00914 |
| | (0.0222) | (0.0655) | (0.0505) | (0.0624) | (0.0184) | (0.0297) | (0.0535) | (0.0480) | (0.0402) | (0.0303) | (0.0237) |
| Labor cost; log | 0.269*** | 0.508** | 0.265*** | 0.262*** | 0.160*** | 0.348*** | 0.316*** | 0.390*** | 0.302*** | 0.348*** | 0.138*** |
| | (0.0389) | (0.196) | (0.0517) | (0.0750) | (0.0418) | (0.0786) | (0.0770) | (0.0793) | (0.0834) | (0.0757) | (0.0326) |
| Material cost; log | 0.616*** | 0.447*** | 0.464*** | 0.684*** | 0.780*** | 0.590*** | 0.546*** | 0.453*** | 0.633*** | 0.575*** | 0.877*** |
| | (0.0368) | (0.152) | (0.0364) | (0.0694) | (0.0368) | (0.0821) | (0.0950) | (0.0645) | (0.0808) | (0.0944) | (0.0324) |
| **Province** | | | | | | | | | | | |
| Hai Phong (mun.) | 0.125 | | 0.0481 | 0.784* | 0.214 | -0.661** | 0.148 | -0.159 | 0.166 | -0.00594 | -0.00619 |
| | (0.126) | | (0.221) | (0.379) | (0.142) | (0.321) | (0.186) | (0.303) | (0.195) | (0.189) | (0.0992) |
| Ha Tay (before merge) | -0.155 | -0.533 | 0.501* | | 0.0640 | -0.531** | | -0.123 | 0.230 | -0.639** | -0.0740 |
| | (0.122) | (0.400) | (0.263) | | (0.149) | (0.236) | | (0.230) | (0.261) | (0.244) | (0.101) |

*cont.*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 | Group 9 | Group 10 | Group 11 |
| Bac Ninh | | | 0.557*** | 0.421 | 0.0102 | -0.419* | | 0.0237 | -0.197 | 0.0738 | |
| | | | (0.198) | (0.356) | (0.142) | (0.228) | | (0.339) | (0.132) | (0.168) | |
| Hai Duong | 0.360 | 0.0419 | 0.110 | 0.0368 | -0.229 | -0.376 | -0.228 | -0.248 | 0.0619 | -0.260* | |
| | (0.267) | (0.807) | (0.300) | (0.392) | (0.148) | (0.243) | (0.266) | (0.418) | (0.426) | (0.153) | |
| Nam Dinh | -0.0858 | -0.221 | -0.211 | 0.199 | -0.0477 | -0.429* | -0.0665 | -0.0717 | | -0.244 | 0.0182 |
| | (0.216) | (0.217) | (0.553) | (0.228) | (0.128) | (0.217) | (0.314) | (0.278) | | (0.216) | (0.151) |
| Quang Ninh | | | | | 0.0159 | | | -0.252 | -0.302** | | |
| | | | | | (0.155) | | | (0.281) | (0.142) | | |
| Thanh Hoa | -0.0116 | -0.156 | 0.000263 | | 0.0869 | -0.498* | -0.122 | -0.393 | 0.0134 | -0.177 | 0.0866 |
| | (0.176) | (0.218) | (0.266) | | (0.208) | (0.296) | (0.233) | (0.254) | (0.197) | (0.163) | (0.116) |
| Nghe An | 0.0398 | | 0.163 | 0.411 | 0.0244 | -0.409* | 0.0924 | 0.292 | -0.00140 | -0.0408 | |
| | (0.187) | | (0.343) | (0.271) | (0.144) | (0.216) | (0.330) | (0.374) | (0.242) | (0.182) | |
| Ha Tinh | 0.165 | -0.424 | 0.986*** | | 0.111 | 1.450*** | | 0.0147 | 0.178 | -0.155 | 0.0276 |
| | (0.124) | (0.264) | (0.185) | | (0.176) | (0.275) | | (0.239) | (0.176) | (0.200) | (0.150) |
| Thua Thien Hue | 0.0706 | -0.489 | 0.0147 | 0.368 | 0.0563 | 0.662*** | 0.167 | | -0.131 | -0.159 | -0.119 |
| | (0.205) | (0.566) | (0.166) | (0.233) | (0.140) | (0.222) | (0.149) | | (0.180) | (0.196) | (0.0958) |

*cont.*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 | Group 9 | Group 10 | Group 11 |
| Da Nang (mun.) | -0.162 | -0.300 | -0.0521 | 0.199 | -0.136 | -0.609** | 0.999* | -0.357 | 0.141 | 0.123 | 0.0589 |
| | (0.149) | (0.387) | (0.272) | (0.215) | (0.142) | (0.255) | (0.578) | (0.298) | (0.187) | (0.348) | (0.128) |
| Quang Nam | 0.0970 | | 0.316* | 2.511*** | -0.0113 | -0.535** | -0.214 | -0.312 | | | 0.350*** |
| | (0.107) | | (0.184) | (0.561) | (0.119) | (0.222) | (0.275) | (0.237) | | | (0.118) |
| Quang Ngai | 0.0835 | | | | -0.222 | | -0.00991 | -0.240 | | | 0.0384 |
| | (0.116) | | | | (0.147) | | (0.209) | (0.347) | | | (0.114) |
| Binh Dinh | 0.126 | -1.562*** | 0.132 | | -0.0308 | -0.566** | -0.106 | -0.0288 | -0.0450 | | |
| | (0.161) | (0.354) | (0.186) | | (0.124) | (0.227) | (0.174) | (0.412) | (0.197) | | |
| Khanh Hoa | 0.290** | 0.557*** | 0.100 | | -0.0409 | -0.577** | 0.131 | | -0.276* | -0.00533 | 0.138 |
| | (0.142) | (0.170) | (0.287) | | (0.139) | (0.262) | (0.182) | | (0.145) | (0.128) | (0.184) |
| Ho Chi Minh (mun.) | 0.162 | -0.121 | 0.243 | 0.439* | 0.00556 | -0.330 | 0.0786 | -0.185 | 0.230 | -0.145 | 0.108 |
| | (0.130) | (0.279) | (0.190) | (0.221) | (0.122) | (0.235) | (0.162) | (0.252) | (0.172) | (0.128) | (0.108) |
| Binh Duong | -0.00684 | 0.552 | 0.374 | 0.368 | 0.0945 | -0.471* | 0.304 | -0.330 | 0.611 | 0.0479 | 0.162 |
| | (0.185) | (0.657) | (0.309) | (0.218) | (0.204) | (0.259) | (0.184) | (0.253) | (0.523) | (0.156) | (0.126) |
| Dong Nai | 0.247 | 0.174 | -0.287 | -0.102 | 0.0547 | -0.148 | 0.757 | -0.0157 | 0.264 | -0.120 | 0.308** |
| | (0.211) | (0.240) | (0.229) | (0.392) | (0.193) | (0.204) | (0.666) | (0.275) | (0.210) | (0.136) | (0.116) |

*cont.*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 | Group 9 | Group 10 | Group 11 |
| Ba Ria - Vung Tau | 0.339 | | 0.0343 | 0.0844 | | | | | 0.517*** | | |
| | (0.281) | | (0.276) | (0.249) | | | | | (0.177) | | |
| Long An | -0.0168 | 0.0366 | 0.210 | -0.0534 | -0.176 | -0.443* | 0.0445 | -0.196 | 0.0510 | -0.163 | |
| | (0.144) | (0.393) | (0.219) | (0.367) | (0.125) | (0.246) | (0.205) | (0.415) | (0.185) | (0.157) | |
| Dong Thap | 0.482 | | | | | | | | | | -1.063*** |
| | (0.391) | | | | | | | | | | (0.108) |
| An Giang | 0.246* | | 0.376** | 0.214 | | | | | 0.172 | | |
| | (0.140) | | (0.169) | (0.242) | | | | | (0.134) | | |
| Tien Giang | 0.269 | -0.889 | 0.550* | | | | -0.451** | -0.161 | 0.610** | | |
| | (0.185) | (0.785) | (0.297) | | | | (0.225) | (0.279) | (0.300) | | |
| Can Tho (mun.) | 0.342** | | 0.298 | -0.0261 | | -0.378 | -0.183 | -0.172 | -0.0515 | -0.677 | -0.0460 |
| | (0.139) | | (0.383) | (0.254) | | (0.278) | (0.371) | (0.457) | (0.192) | (0.410) | (0.108) |
| **Survey** | | | | | | | | | | | |
| 2015 | 0.394*** | 0.476 | 0.497*** | 0.303 | 0.329** | -0.191 | 0.291* | 0.324*** | 0.321*** | 0.407* | 0.862*** |
| | (0.0922) | (0.375) | (0.112) | (0.232) | (0.130) | (0.207) | (0.157) | (0.113) | (0.104) | (0.209) | (0.165) |

*cont.*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 | Group 9 | Group 10 | Group 11 |
| Constant | 1.731*** | 2.031* | 2.057*** | 0.474 | 1.086** | 1.923*** | 1.785*** | 0.881 | 1.097** | 0.418 | 0.462 |
| | (0.404) | (1.091) | (0.754) | (0.615) | (0.477) | (0.578) | (0.629) | (0.790) | (0.549) | (0.509) | (0.357) |
| Observations | 237 | 55 | 181 | 40 | 159 | 75 | 134 | 188 | 149 | 104 | 54 |
| R-squared | 0.957 | 0.892 | 0.890 | 0.980 | 0.951 | 0.975 | 0.916 | 0.879 | 0.909 | 0.961 | 0.995 |
| $\alpha_K + \alpha_L + \alpha_M$ | 0.96 | 0.97 | 0.94 | 1.01 | 0.98 | 0.98 | 0.97 | 1.03 | 0.99 | 1.05 | 1.01 |
| CRS F-stat | 3.06* | 0.16 | 2.25 | 0.07 | 0.44 | 0.35 | 0.93 | 0.45 | 0.11 | 4.51** | 0.09 |

*Note:* Sector group definition: Group 1 = Food, beverages & tobacco (ISIC code 15,16); Group 2 = Textiles (17); Group 3 = Garments (18); Group 4 = Leather products (19); Group 5 = Wooden products & furniture (20, 36); Group 6 = Paper, printing & publishing (21 & 22); Group 7 = Refined petroleum products, chemicals, plastic & rubber (23 - 25); Group 8 = Non-metallic mineral products (26); Group 9 = Basic metal & Fabricated metal products (27 & 28); Group 10 = machinery, office, electronics & precision instruments (29 - 33); Group 11 = Transport machines (34).

The reference group for fixed effects is firms that are located in Hanoi (mun. cap.), and surveyed in 2005. The dependent variable is the log of revenues. Standard errors in parentheses. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

# Table 2.B1: Temperature interpolation - MLR

| | Temperature ($^0C$) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
| ARIABLES | All | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| **Year 2004** | | | | | | | | | | | | | |
| Latitude | -0.400*** | -0.780*** | -0.718*** | -0.562*** | -0.403*** | -0.287*** | -0.118*** | -0.0853*** | -0.0230*** | -0.192*** | -0.394*** | -0.534*** | -0.713*** |
| | (0.00609) | (0.0195) | (0.0225) | (0.0154) | (0.0143) | (0.0125) | (0.00774) | (0.00746) | (0.00655) | (0.00794) | (0.00930) | (0.0149) | (0.0181) |
| Longitude | -0.0275*** | -0.246*** | -0.171*** | -0.309*** | -0.160*** | 0.0447*** | 0.159*** | 0.152*** | 0.154*** | 0.144*** | 0.0501*** | -0.0169 | -0.132*** |
| | (0.00792) | (0.0236) | (0.0279) | (0.0235) | (0.0193) | (0.0160) | (0.0109) | (0.00955) | (0.00919) | (0.0113) | (0.0113) | (0.0185) | (0.0224) |
| Altitude (km) | -1.629*** | -1.355*** | -1.986*** | -1.072*** | -1.923*** | -1.469*** | -1.565*** | -1.675*** | -1.725*** | -1.833*** | -1.643*** | -1.785*** | -1.563*** |
| | (0.0873) | (0.230) | (0.320) | (0.255) | (0.217) | (0.196) | (0.119) | (0.0977) | (0.0757) | (0.115) | (0.125) | (0.204) | (0.227) |
| Distance to sea (km) | -0.00659*** | -0.00705*** | -0.00283*** | -0.00320*** | -0.00441*** | -0.00602*** | -0.00736*** | -0.00694*** | -0.00804*** | -0.00695*** | -0.00829*** | -0.00818*** | -0.00959*** |
| | (0.000264) | (0.000776) | (0.000963) | (0.000768) | (0.000626) | (0.000539) | (0.000346) | (0.000289) | (0.000251) | (0.000339) | (0.000359) | (0.000615) | (0.000742) |
| Constant | 34.55*** | 60.31*** | 51.61*** | 66.06*** | 49.89*** | 26.98*** | 12.50*** | 12.71*** | 11.74*** | 14.52*** | 26.36*** | 34.61*** | 47.56*** |
| | (0.844) | (2.523) | (2.943) | (2.496) | (2.054) | (1.697) | (1.155) | (0.998) | (0.958) | (1.208) | (1.211) | (1.967) | (2.396) |
| Observations | 24,156 | 2,046 | 1,914 | 2,046 | 1,980 | 2,046 | 1,980 | 2,046 | 2,046 | 1,980 | 2,046 | 1,980 | 2,046 |
| R-squared | 0.561 | 0.796 | 0.688 | 0.666 | 0.698 | 0.697 | 0.808 | 0.825 | 0.849 | 0.847 | 0.883 | 0.817 | 0.822 |
| **Year 2014** | | | | | | | | | | | | | |
| Latitude | -0.398*** | -0.746*** | -0.748*** | -0.550*** | -0.330*** | -0.233*** | -0.0969*** | -0.0403*** | -0.0600*** | -0.122*** | -0.310*** | -0.551*** | -1.005*** |
| | (0.00663) | (0.0154) | (0.0235) | (0.0156) | (0.0105) | (0.0108) | (0.00662) | (0.00702) | (0.00701) | (0.00780) | (0.00874) | (0.0128) | (0.0160) |
| Longitude | -0.00549 | -0.0804*** | -0.262*** | -0.233*** | -0.121*** | -0.00481 | 0.101*** | 0.154*** | 0.174*** | 0.140*** | 0.0995*** | 0.00682 | -0.0608*** |
| | (0.00859) | (0.0221) | (0.0313) | (0.0232) | (0.0152) | (0.0135) | (0.00979) | (0.0105) | (0.0101) | (0.0103) | (0.0110) | (0.0164) | (0.0207) |
| Altitude (km) | -1.253*** | -0.880*** | -0.912*** | -1.239*** | -0.961*** | -0.953*** | -1.451*** | -1.683*** | -1.845*** | -1.805*** | -1.728*** | -1.294*** | -0.262 |
| | (0.0916) | (0.233) | (0.318) | (0.236) | (0.189) | (0.182) | (0.0905) | (0.0796) | (0.103) | (0.105) | (0.110) | (0.157) | (0.203) |
| Distance to sea (km) | -0.00614*** | -0.00586*** | -0.00279*** | -0.00257*** | -0.00491*** | -0.00610*** | -0.00815*** | -0.00738*** | -0.00703*** | -0.00663*** | -0.00742*** | -0.00829*** | -0.00636*** |
| | (0.000285) | (0.000692) | (0.00103) | (0.000758) | (0.000500) | (0.000465) | (0.000283) | (0.000273) | (0.000312) | (0.000317) | (0.000346) | (0.000523) | (0.000635) |
| Constant | 32.04*** | 40.55*** | 61.13*** | 57.69*** | 44.55*** | 31.92*** | 19.08*** | 11.95*** | 9.816*** | 14.17*** | 20.39*** | 32.52*** | 43.00*** |
| | (0.914) | (2.353) | (3.358) | (2.478) | (1.632) | (1.442) | (1.028) | (1.095) | (1.061) | (1.082) | (1.172) | (1.766) | (2.202) |
| Observations | 24,090 | 2,046 | 1,848 | 2,046 | 1,980 | 2,046 | 1,980 | 2,046 | 2,046 | 1,980 | 2,046 | 1,980 | 2,046 |
| R-squared | 0.497 | 0.803 | 0.651 | 0.670 | 0.691 | 0.674 | 0.845 | 0.820 | 0.819 | 0.828 | 0.874 | 0.854 | 0.861 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

## Table 2.B2: Rainfall interpolation - MLR

| | Monthly rainfall (mm); log | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
| ARIABLES | All | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| **Double log regression** | | | | | | | | | | | | | |
| Latitude; log | 0.355*** | 2.058*** | 2.609*** | 1.172*** | 0.339*** | 0.220*** | 0.342*** | 0.241*** | 0.219*** | -0.565*** | -1.820*** | -0.996*** | 0.441*** |
| | (0.0178) | (0.0529) | (0.0447) | (0.0484) | (0.0318) | (0.0281) | (0.0357) | (0.0350) | (0.0329) | (0.0346) | (0.0390) | (0.0586) | (0.0563) |
| Longitude; log | 4.012*** | 9.635*** | 4.169*** | 4.611*** | 5.638*** | 3.456*** | 3.613*** | 1.800*** | 0.399* | -2.497*** | -4.698*** | 6.838*** | 15.17*** |
| | (0.160) | (0.473) | (0.414) | (0.407) | (0.261) | (0.202) | (0.252) | (0.236) | (0.221) | (0.211) | (0.367) | (0.503) | (0.485) |
| Altitude (km); log | 0.265*** | 0.620*** | 0.00366 | -0.217*** | -0.0401* | -0.204*** | -0.0784*** | 0.317*** | 0.173*** | -0.0885*** | 0.441*** | 1.167*** | 1.089*** |
| | (0.0152) | (0.0460) | (0.0384) | (0.0401) | (0.0237) | (0.0200) | (0.0252) | (0.0230) | (0.0214) | (0.0227) | (0.0349) | (0.0517) | (0.0477) |
| Distance to sea (km); log | -0.0910*** | -0.437*** | -0.278*** | -0.0678*** | 0.125*** | 0.135*** | 0.137*** | 0.100*** | 0.0784*** | -0.0201*** | -0.198*** | -0.332*** | -0.335*** |
| | (0.00483) | (0.0147) | (0.0126) | (0.0129) | (0.00995) | (0.00823) | (0.00949) | (0.00937) | (0.00852) | (0.00761) | (0.0106) | (0.0151) | (0.0151) |
| Constant | -15.25*** | -46.71*** | -22.80*** | -21.22*** | -23.56*** | -12.22*** | -13.24*** | -4.261*** | 2.532** | 18.65*** | 32.46*** | -24.41*** | -68.22*** |
| | (0.740) | (2.198) | (1.927) | (1.890) | (1.240) | (0.942) | (1.173) | (1.108) | (1.043) | (0.996) | (1.723) | (2.309) | (2.225) |
| Observations | 217,440 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 |
| R-squared | 0.011 | 0.198 | 0.209 | 0.055 | 0.049 | 0.040 | 0.041 | 0.047 | 0.033 | 0.045 | 0.175 | 0.090 | 0.157 |
| **Semi log regression** | | | | | | | | | | | | | |
| Latitude | 0.0232*** | 0.130*** | 0.174*** | 0.0794*** | 0.0278*** | 0.0174*** | 0.0226*** | 0.0175*** | 0.0120*** | -0.0423*** | -0.117*** | -0.0649*** | 0.0230*** |
| | (0.00111) | (0.00318) | (0.00261) | (0.00300) | (0.00188) | (0.00162) | (0.00206) | (0.00198) | (0.00189) | (0.00195) | (0.00241) | (0.00360) | (0.00339) |
| Longitude | 0.0335*** | 0.0802*** | -0.0110** | 0.00906** | 0.0329*** | 0.0210*** | 0.0310*** | 0.0100*** | 0.00191 | -0.0183*** | -0.0192*** | 0.0985*** | 0.166*** |
| | (0.00180) | (0.00518) | (0.00445) | (0.00454) | (0.00278) | (0.00214) | (0.00281) | (0.00265) | (0.00249) | (0.00228) | (0.00391) | (0.00553) | (0.00513) |
| Altitude (km) | 0.154*** | 0.356*** | 0.0713*** | -0.0818*** | -0.00726 | -0.125*** | -0.0775*** | 0.166*** | 0.0747*** | -0.0481*** | 0.265*** | 0.665*** | 0.593*** |
| | (0.00967) | (0.0299) | (0.0242) | (0.0248) | (0.0142) | (0.0123) | (0.0155) | (0.0138) | (0.0133) | (0.0142) | (0.0232) | (0.0337) | (0.0311) |
| Distance to sea (km) | -0.000586*** | -0.00252*** | -0.00285*** | -0.00137*** | 8.14e-05 | 0.000406*** | 0.000719*** | 0.000413*** | 0.000436*** | -1.03e-05 | -0.000463*** | -0.000833*** | -0.00105*** |
| | (3.86e-05) | (0.000113) | (9.54e-05) | (0.000101) | (5.85e-05) | (4.51e-05) | (5.51e-05) | (5.34e-05) | (5.10e-05) | (4.81e-05) | (7.85e-05) | (0.000115) | (0.000107) |
| Constant | 0.184 | -8.349*** | 1.303*** | 1.140** | 0.300 | 2.560*** | 1.437*** | 3.881*** | 4.920*** | 7.986*** | 8.643*** | -6.023*** | -15.59*** |
| | (0.186) | (0.537) | (0.464) | (0.469) | (0.294) | (0.220) | (0.291) | (0.278) | (0.262) | (0.241) | (0.411) | (0.564) | (0.521) |
| Observations | 217,440 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 | 18,120 |
| R-squared | 0.011 | 0.184 | 0.227 | 0.061 | 0.033 | 0.020 | 0.031 | 0.036 | 0.024 | 0.059 | 0.159 | 0.063 | 0.136 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

## Table 2.C1: Robustness check: Alternative IVs

| | Survey 2005, $\rho$ = 1 | | | | | | Survey 2015, $\rho$ = 10 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLE | *Baseline* | *Geodetic* | *Realproduction* | *Noupcap* | *7month* | *Timedummy* | *Baseline* | *Geodetic* | *Realproduction* | *Noupcap* | *7month* | *Timedummy* |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| **Panel A: Performance** | | | | | | | | | | | | |
| **Revenue; log** | | | | | | | | | | | | |
| Outage *(Vol)*; log | -0.27 | -0.30 | 0.37 | -0.23 | -0.36 | -0.32 | -0.73*** | -0.73*** | -0.51** | -0.49** | -0.73*** | -0.68*** |
| | (0.44) | (0.44) | (1.14) | (0.44) | (0.53) | (0.46) | (0.25) | (0.24) | (0.21) | (0.23) | (0.25) | (0.26) |
| Observations | 1,132 | 1,132 | 1,132 | 1,132 | 1,132 | 1,132 | 915 | 915 | 915 | 915 | 915 | 915 |
| First stage F-statistic | 14.32 | 13.06 | 1.61 | 14.60 | 14.11 | 13.27 | 17.68 | 18.28 | 17.25 | 15.36 | 17.68 | 10.30 |
| SW $\chi^2$ test | 15.46*** | 14.10*** | 1.74 | 15.76*** | 15.23*** | 14.33*** | 19.54*** | 20.20*** | 19.07*** | 16.98*** | 19.54*** | 11.38*** |
| AR $\chi^2$ test | 0.45 | 0.58 | 0.15 | 0.32 | 0.54 | 0.55 | 5.67** | 5.68** | 3.01* | 2.33 | 5.67** | 4.13** |
| **TFP YKL model; log** | | | | | | | | | | | | |
| Outage *(Vol)*; log | -0.25 | -0.27 | -0.01 | -0.24 | -0.33 | -0.27 | -0.55** | -0.53** | -0.58*** | -0.46** | -0.55** | -0.61* |
| | (0.22) | (0.22) | (0.39) | (0.21) | (0.27) | (0.23) | (0.23) | (0.23) | (0.21) | (0.19) | (0.23) | (0.37) |
| Observations | 977 | 977 | 977 | 977 | 977 | 977 | 421 | 421 | 421 | 421 | 421 | 421 |
| First stage F-statistic | 9.59 | 8.92 | 2.94 | 9.90 | 8.22 | 8.95 | 3.62 | 3.67 | 3.90 | 3.86 | 3.62 | 1.58 |
| SW $\chi^2$ test | 10.36*** | 9.63*** | 3.17* | 10.69*** | 8.88*** | 9.67*** | 4.15** | 4.21** | 4.46** | 4.42** | 4.15** | 1.81 |
| AR $\chi^2$ test | 2.50 | 2.81* | 0 | 2.35 | 3.10* | 2.26 | 3.97** | 3.88** | 5.13** | 3.14* | 3.97** | 2.57 |
| **TFP YKLM model; log** | | | | | | | | | | | | |

*(cont.)*

| VARIABLE | Survey 2005, $\rho$ = 1 | | | | | | Survey 2015, $\rho$ = 10 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Baseline* | *Geodetic* | *Realproduction* | *Noupcap* | *7month* | *Timedummy* | *Baseline* | *Geodetic* | *Realproduction* | *Noupcap* | *7month* | *Timedummy* |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Outage *(Vol)*; log | -0.13* | -0.16** | 0.04 | -0.12* | -0.21** | -0.11 | -0.53 | -0.52 | -0.33 | -0.49* | -0.53 | -0.57 |
| | (0.07) | (0.07) | (0.23) | (0.07) | (0.08) | (0.09) | (0.41) | (0.41) | (0.30) | (0.28) | (0.41) | (0.65) |
| Observations | 966 | 966 | 966 | 966 | 966 | 966 | 392 | 392 | 392 | 392 | 392 | 392 |
| First stage F-statistic | 9.01 | 8.43 | 2.97 | 9.26 | 7.85 | 8.46 | 2.71 | 2.76 | 2.45 | 2.65 | 2.71 | 1.03 |
| SW $\chi^2$ test | 9.73*** | 9.10*** | 3.21* | 10.01*** | 8.48*** | 9.14*** | 3.13* | 3.18* | 2.83* | 3.05* | 3.13* | 1.19 |
| AR $\chi^2$ test | 3.66* | 5.96** | 0.04 | 3.57* | 7.07*** | 1.50 | 4.66** | 4.64** | 1.47 | 6.25** | 4.66** | 1.53 |

## Panel B: Energy inputs

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Generator use; log** | | | | | | | | | | | | |
| Outage *(Vol)*; log | 0.35*** | 0.36*** | -0.48 | 0.31*** | 0.22** | 0.49** | 0.31*** | 0.31*** | 0.28*** | 0.23** | 0.31*** | 0.37*** |
| | (0.11) | (0.10) | (0.86) | (0.09) | (0.09) | (0.20) | (0.10) | (0.09) | (0.10) | (0.10) | (0.10) | (0.12) |
| Observations | 1,035 | 1,035 | 1,035 | 1,035 | 1,035 | 1,035 | 605 | 605 | 605 | 605 | 605 | 605 |
| First stage F-statistic | 11.38 | 10.69 | 1.58 | 11.56 | 10.34 | 10.40 | 10.14 | 10.56 | 10.73 | 8.58 | 10.14 | 8.81 |
| SW $\chi^2$ test | 12.28*** | 11.54*** | 1.71 | 12.48*** | 11.16*** | 11.23*** | 11.34*** | 11.81*** | 12.00*** | 9.60*** | 11.34*** | 9.85*** |
| AR $\chi^2$ test | 8.26*** | 8.39*** | 0.87 | 8.15*** | 4.84** | 9.20*** | 6.49** | 6.82*** | 5.17** | 2.72* | 6.49** | 10.32*** |
| **Energy cost; log** | | | | | | | | | | | | |
| Outage *(Vol)*; log | -0.76** | -0.78** | 0.66 | -0.73** | -0.95** | -0.97** | | | | | | |
| | (0.33) | (0.33) | (1.57) | (0.33) | (0.42) | (0.40) | | | | | | |
| Observations | 1,136 | 1,136 | 1,136 | 1,136 | 1,136 | 1,136 | | | | | | |
| First stage F-statistic | 16.47 | 14.90 | 1.68 | 16.76 | 16.46 | 14.90 | | | | | | |

*(cont.)*

| | Survey 2005, $\rho$ = 1 | | | | | | Survey 2015, $\rho$ = 10 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLE | *Baseline* | *Geodetic* | *Realproduction* | *Noupcap* | *7month* | *Timedummy* | *Baseline* | *Geodetic* | *Realproduction* | *Noupcap* | *7month* | *Timedummy* |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| SW $\chi^2$ test | 17.78*** | 16.09*** | 1.82 | 18.10*** | 17.77*** | 16.09*** | | | | | | |
| AR $\chi^2$ test | 7.63*** | 8.66*** | 0.30 | 7.26*** | 8.14*** | 9.74*** | | | | | | |
| **Electric cost; log** | | | | | | | | | | | | |
| Outage *(Vol)*; log | | | | | | | -1.03** | -1.04** | -1.06*** | -1.11*** | -1.03** | -1.15*** |
| | | | | | | | (0.43) | (0.43) | (0.32) | (0.29) | (0.43) | (0.44) |
| Observations | | | | | | | 841 | 841 | 841 | 841 | 841 | 841 |
| First stage F-statistic | | | | | | | 19.32 | 19.97 | 20.32 | 17.92 | 19.32 | 11.01 |
| SW $\chi^2$ test | | | | | | | 21.44*** | 22.16*** | 22.55*** | 19.88*** | 21.44*** | 12.22*** |
| AR $\chi^2$ test | | | | | | | 9.31*** | 9.63*** | 11.90*** | 15.51*** | 9.31*** | 9.17*** |
| **Fuel cost; log** | | | | | | | | | | | | |
| Outage *(Vol)*; log | | | | | | | -0.62 | -0.64 | -0.64 | -0.64 | -0.62 | -1.08 |
| | | | | | | | (0.55) | (0.55) | (0.41) | (0.42) | (0.55) | (0.76) |
| Observations | | | | | | | 458 | 458 | 458 | 458 | 458 | 458 |
| First stage F-statistic | | | | | | | 13.59 | 13.93 | 10.63 | 8.58 | 13.59 | 6.11 |
| SW $\chi^2$ test | | | | | | | 15.57*** | 15.96*** | 12.18*** | 9.83*** | 15.57*** | 7.00*** |
| AR $\chi^2$ test | | | | | | | 1.78 | 1.88 | 3.61* | 3.81* | 1.78 | 5.13** |

## Panel C: Other inputs

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Material cost; log** | | | | | | | | | | | | |
| Outage *(Vol)*; log | -0.27 | -0.30 | 0.03 | -0.23 | -0.32 | -0.32 | -0.62 | -0.60 | -0.85* | -0.62* | -0.62 | -0.67 |

*(cont.)*

| | Survey 2005, $\rho$ = 1 | | | | | | Survey 2015, $\rho$ = 10 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLE | *Baseline* | *Geodetic* | *Realproduction* | *Noupcap* | *7month* | *Timedummy* | *Baseline* | *Geodetic* | *Realproduction* | *Noupcap* | *7month* | *Timedummy* |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| | (0.70) | (0.68) | (0.92) | (0.69) | (0.84) | (0.74) | (0.40) | (0.39) | (0.46) | (0.38) | (0.40) | (0.50) |
| Observations | 1,124 | 1,124 | 1,124 | 1,124 | 1,124 | 1,124 | 529 | 529 | 529 | 529 | 529 | 529 |
| First stage F-statistic | 13.63 | 12.43 | 1.62 | 13.84 | 13.36 | 12.74 | 8.85 | 9.13 | 8.91 | 7.49 | 8.85 | 6.30 |
| SW $\chi^2$ test | 14.72*** | 13.43*** | 1.75 | 14.95*** | 14.43*** | 13.76*** | 10.03*** | 10.34*** | 10.09*** | 8.48*** | 10.03*** | 7.14*** |
| AR $\chi^2$ test | 0.17 | 0.23 | 0 | 0.12 | 0.16 | 0.22 | 3.34* | 3.22* | 3.71* | 2.97* | 3.34* | 2.25 |
| **Labor cost; log** | | | | | | | | | | | | |
| Outage *(Vol)*; log | 0.04 | 0.01 | 0.34 | 0.06 | -0.01 | 0.02 | -0.64 | -0.63 | -0.62 | -0.72* | -0.64 | -0.72 |
| | (0.18) | (0.19) | (0.53) | (0.18) | (0.22) | (0.19) | (0.52) | (0.51) | (0.38) | (0.40) | (0.52) | (0.56) |
| Observations | 1,129 | 1,129 | 1,129 | 1,129 | 1,129 | 1,129 | 845 | 845 | 845 | 845 | 845 | 845 |
| First stage F-statistic | 13.45 | 12.55 | 1.60 | 13.80 | 12.87 | 12.87 | 14.10 | 14.56 | 14.73 | 13.64 | 14.10 | 8.35 |
| SW $\chi^2$ test | 14.52*** | 13.55*** | 1.73 | 14.90*** | 13.90*** | 13.90*** | 15.64*** | 16.16*** | 16.34*** | 15.13*** | 15.64*** | 9.26*** |
| AR $\chi^2$ test | 0.04 | 0.01 | 0.73 | 0.08 | 0 | 0.01 | 2.75* | 2.68 | 5.48** | 8.12*** | 2.75* | 3.41* |

The regressions include control variables as those in Table 2.9, and dummies for sectors. The dependent variables are in bold. The endogenous variable is power outage volume (*Vol*). **First stage F-statistic:** Kleibergen-Paap rk Wald F-statistic that is robust to heteroskedasticity. **Underidentification test:** SW $\chi^2$ test (Sanderson-Windmeijer first stage $\chi^2$ test). **Weak-instrument robust tests for significant endogenous variables** : AR $\chi^2$ test (Anderson-Rubin Wald $\chi^2$ test). Robust standard errors clustered at the province level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

## Table 2.C2: Robustness check : Sale loss, and firm heterogeneity

| Sample | First stage *HAI(ρ)* (1) | (2) | *F-statistic* (3) | Second stage *Outage (Vol); log* (4) | (5) | *Obs* (6) | *Cluster* (7) | *SW $\chi^2$ test* (8) | *AR $\chi^2$ test* (9) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | **Panel A: Survey 2005** ($\rho$ = 1) | | | | | |
| Baseline (Whole sample) | -11.65*** | (3.08) | 14.32 | -0.27 | (0.44) | 1,132 | 24 | 15.46*** | 0.45 |
| Manufacturers | -11.67*** | (3.18) | 13.50 | -0.28 | (0.44) | 1,119 | 24 | 14.52*** | 0.50 |
| Generator | -12.44*** | (3.58) | 12.09 | 0.14 | (0.42) | 379 | 24 | 13.78*** | 0.09 |
| Non-generator | -8.83** | (3.50) | 6.38 | -0.86 | (0.53) | 734 | 24 | 6.98*** | 4.14** |
| Elec-intensive | -11.28*** | (3.40) | 11.01 | -0.42 | (0.53) | 874 | 24 | 11.86*** | 0.79 |
| Non-Elec-intensive | -13.27*** | (5.08) | 6.82 | -0.01 | (0.42) | 258 | 24 | 7.95*** | 0 |
| Exporters | -17.90*** | (4.71) | 14.45 | -0.39 | (0.31) | 524 | 24 | 16.10*** | 2.63 |
| Non-exporters | -6.07** | (2.63) | 5.32 | 0.37 | (0.80) | 608 | 24 | 5.92** | 0.24 |
| | | | | **Survey 2015** ($\rho$ = 10) | | | | | |
| Baseline (Whole sample) | -1.76*** | (0.42) | 17.68 | -0.73*** | (0.25) | 915 | 19 | 19.54*** | 5.67** |
| Manufacturers | -1.94*** | (0.55) | 12.36 | -0.88*** | (0.31) | 643 | 19 | 13.78*** | 8.05*** |
| Generator | -1.47** | (0.72) | 4.10 | -1.48** | (0.71) | 224 | 19 | 5.08** | 8.14*** |
| Non-generator | -2.06*** | (0.57) | 13.23 | -0.90*** | (0.25) | 416 | 18 | 15.25*** | 10.84*** |
| Elec-intensive | -1.53*** | (0.55) | 7.72 | -1.32*** | (0.45) | 580 | 19 | 8.59*** | 12.57*** |
| Non-Elec-intensive | -2.29*** | (0.24) | 94.74 | -0.10 | (0.29) | 335 | 18 | 109.49*** | 0.10 |
| Exporters | -2.83*** | (0.80) | 12.61 | -0.82*** | (0.21) | 251 | 18 | 15.82*** | 16.60*** |
| Non-exporters | -1.55*** | (0.33) | 22.36 | -0.51* | (0.26) | 664 | 19 | 25.12*** | 2.22 |

*Note:* The regressions replicate the baseline 2SLS estimates as those in Table 2.7 (first stage), and 2.9 (second stage) for various sub-samples. The dependent variable is revenues (log). The endogenous variable is power outage volume (*Vol*). **First stage F-statistic:** Kleibergen-Paap rk Wald F-statistic that is robust to heteroskedasticity. **Underidentification test:** SW $\chi^2$ test (Sanderson-Windmeijer first stage $\chi^2$ test). **Weak-instrument robust tests for significant endogenous variables** : AR $\chi^2$ test (Anderson-Rubin Wald $\chi^2$ test). Robust standard errors clustered at the province level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

## Table 2.C3: Robustness check: Survey 2015

| | | Handle fiscal year | Weights | | |
|---|---|---|---|---|---|
| VARIABLE | *Baseline* | *Add dummy* | *Weak* | *Median* | *Strong* |
| | (1) | (2) | (3) | (4) | (5) |
| | | **Panel A: Performance** | | | |
| **Revenue; log** | | | | | |
| Power outage; log | -0.73*** | -0.55* | -1.13*** | -1.03** | -1.03** |
| | (0.25) | (0.29) | (0.41) | (0.40) | (0.41) |
| Observations | 915 | 915 | 915 | 915 | 915 |
| First stage HAI(10) | -1.76*** | -1.64*** | -2.13*** | -2.19*** | -2.19*** |
| | (0.42) | (0.41) | (0.49) | (0.46) | (0.47) |
| First stage F-statistic | 17.68 | 15.98 | 18.91 | 22.67 | 22.02 |
| SW $\chi^2$ test | 19.54*** | 17.68*** | 20.90*** | 25.06*** | 24.33*** |
| AR $\chi^2$ test | 5.67** | 3.71* | 5.04** | 4.51** | 4.40** |
| **TFP YKL model; log** | | | | | |
| Power outage; log | -0.55** | -0.34 | -0.15 | -0.11 | -0.09 |
| | (0.23) | (0.27) | (0.18) | (0.17) | (0.17) |
| Observations | 421 | 421 | 421 | 421 | 421 |
| First stage HAI(10) | -1.53* | -1.60** | -4.24*** | -4.37*** | -4.55*** |
| | (0.80) | (0.74) | (0.71) | (0.74) | (0.75) |
| First stage F-statistic | 3.62 | 4.67 | 35.37 | 35.17 | 37.31 |
| SW $\chi^2$ test | 4.15** | 5.37** | 40.52*** | 40.29*** | 42.74*** |
| AR $\chi^2$ test | 3.97** | 1.44 | 0.66 | 0.42 | 0.28 |

*(cont.)*

| | | Handle fiscal year | Weights | | |
|---|---|---|---|---|---|
| VARIABLE | *Baseline* | *Add dummy* | *Weak* | *Median* | *Strong* |
| | (1) | (2) | (3) | (4) | (5) |
| **TFP YKLM model; log** | | | | | |
| Power outage; log | -0.53 | -0.45 | -0.04 | -0.04 | -0.04 |
| | (0.41) | (0.40) | (0.18) | (0.17) | (0.17) |
| Observations | 392 | 392 | 392 | 392 | 392 |
| First stage HAI(10) | -1.50 | -1.43* | -4.44*** | -4.56*** | -4.75*** |
| | (0.91) | (0.80) | (0.80) | (0.83) | (0.84) |
| First stage F-statistic | 2.71 | 3.16 | 31.14 | 30.36 | 32.38 |
| SW $\chi^2$ test | 3.13* | 3.65* | 35.90*** | 35.00*** | 37.33*** |
| AR $\chi^2$ test | 4.66** | 2.83* | 0.07 | 0.05 | 0.04 |

**Panel B: Energy inputs**

| | | | | | |
|---|---|---|---|---|---|
| **Generator use; log** | | | | | |
| Power outage; log | 0.31*** | 0.21 | 0.19** | 0.19** | 0.19** |
| | (0.10) | (0.13) | (0.08) | (0.08) | (0.08) |
| Observations | 605 | 605 | 605 | 605 | 605 |
| First stage HAI(10) | -1.86*** | -1.83*** | -3.93*** | -4.03*** | -4.14*** |
| | (0.58) | (0.58) | (0.55) | (0.53) | (0.52) |
| First stage F-statistic | 10.14 | 10.11 | 52.04 | 57.51 | 62.60 |
| SW $\chi^2$ test | 11.34*** | 11.33*** | 58.21*** | 64.32*** | 70.02*** |
| AR $\chi^2$ test | 6.49** | 2.13 | 4.52** | 5.27** | 5.56** |
| **Electric cost; log** | | | | | |
| Power outage; log | -1.03** | -0.84* | -0.87** | -0.91** | -0.90** |
| | (0.43) | (0.45) | (0.40) | (0.39) | (0.38) |

*(cont.)*

| VARIABLE | *Baseline* | **Handle fiscal year** *Add dummy* | **Weights** *Weak* | *Median* | *Strong* |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Observations | 841 | 841 | 841 | 841 | 841 |
| First stage HAI(10) | -1.85*** | -1.76*** | -2.12*** | -2.18*** | -2.18*** |
| | (0.42) | (0.41) | (0.52) | (0.49) | (0.49) |
| First stage F-statistic | 19.32 | 18.55 | 16.40 | 19.87 | 19.44 |
| SW $\chi^2$ test | 21.44*** | 20.62*** | 18.20*** | 22.05*** | 21.57*** |
| AR $\chi^2$ test | 9.31*** | 5.19** | 7.20*** | 8.45*** | 8.28*** |
| **Fuel cost; log** | | | | | |
| Power outage; log | -0.62 | -0.71 | 0.24 | 0.23 | 0.23 |
| | (0.55) | (0.61) | (0.23) | (0.23) | (0.23) |
| Observations | 458 | 458 | 458 | 458 | 458 |
| First stage HAI(10) | -2.42*** | -2.33*** | -4.48*** | -4.55*** | -4.60*** |
| | (0.66) | (0.63) | (0.50) | (0.54) | (0.54) |
| First stage F-statistic | 13.59 | 13.84 | 79.05 | 69.99 | 72.24 |
| SW $\chi^2$ test | 15.57*** | 15.90*** | 90.58*** | 80.20*** | 82.77*** |
| AR $\chi^2$ test | 1.78 | 1.88 | 0.98 | 0.98 | 0.95 |

**Panel C: Other inputs**

| | | | | | |
|---|---|---|---|---|---|
| **Material cost; log** | | | | | |
| Power outage; log | -0.62 | -0.43 | -0.20 | -0.23 | -0.21 |
| | (0.40) | (0.42) | (0.50) | (0.49) | (0.48) |
| Observations | 529 | 529 | 529 | 529 | 529 |
| First stage HAI(10) | -1.87*** | -1.87*** | -4.01*** | -4.10*** | -4.16*** |
| | (0.63) | (0.58) | (0.76) | (0.76) | (0.76) |

*(cont.)*

| VARIABLE | Baseline | Handle fiscal year<br>Add dummy | Weights<br>Weak | Median | Strong |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| First stage F-statistic | 8.85 | 10.39 | 27.81 | 28.91 | 29.56 |
| SW $\chi^2$ test | 10.03*** | 11.79*** | 31.50*** | 32.75*** | 33.49*** |
| AR $\chi^2$ test | 3.34* | 1.29 | 0.17 | 0.23 | 0.20 |
| **Labor cost; log** | | | | | |
| Power outage; log | -0.64 | -0.74 | -0.15 | -0.16 | -0.13 |
| | (0.52) | (0.58) | (0.34) | (0.33) | (0.32) |
| Observations | 845 | 845 | 845 | 845 | 845 |
| First stage HAI(10) | -1.62*** | -1.48*** | -1.91*** | -1.98*** | -1.98*** |
| | (0.43) | (0.42) | (0.44) | (0.41) | (0.41) |
| First stage F-statistic | 14.10 | 12.33 | 18.76 | 23.57 | 22.70 |
| SW $\chi^2$ test | 15.64*** | 13.70*** | 20.82*** | 26.15*** | 25.19*** |
| AR $\chi^2$ test | 2.75* | 2.70 | 0.23 | 0.26 | 0.19 |

The regressions include control variables as those in Table 2.9, and dummies for sectors. The dependent variables are in bold. The endogenous variable is power outage volume (*Vol*). **First stage F-statistic:** Kleibergen-Paap rk Wald F-statistic that is robust to heteroskedasticity. **Underidentification test:** SW $\chi^2$ test (Sanderson-Windmeijer first stage $\chi^2$ test). **Weak-instrument robust tests for significant endogenous variables** : AR $\chi^2$ test (Anderson-Rubin Wald $\chi^2$ test). Robust standard errors clustered at the provincea level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

# References


Ackerberg, D. A., Caves, K. and Frazer, G. (2015), 'Identification Properties of Recent Production Function Estimators', *Econometrica* **83**(6), 2411–2451.
**URL:** *http://dx.doi.org/10.3982/ECTA13408*

Ackerberg, D., Lanier Benkard, C., Berry, S. and Pakes, A. (2007), *Chapter 63 Econometric Tools for Analyzing Market Outcomes*, Vol. 6, Elsevier, pp. 4171–4276.
**URL:** *http://www.sciencedirect.com/science/article/pii/S1573441207060631*

ADB (2011), Energy for all: Viet Nam's success in increasing access to energy through rural electrification, Report, Asian Development Bank.
**URL:** *https://think-asia.org/bitstream/handle/11540/963/rural-electrification-vie.pdf?sequence=1*

ADB (2015*a*), Assessment of Power Sector Reforms in Viet Nam - Country Report, Report, Asian Developement Bank.
**URL:** *https://www.adb.org/sites/default/files/institutional-document/173769/vie-power-sector-reforms.pdf*

ADB (2015*b*), Viet Nam Energy sector assessment, strategy, and roadmap, Report.
**URL:** *https://www.adb.org/sites/default/files/institutional-document/178616/vie-energy-road-map.pdf*

Adenikinju, A. F. (2003), 'Electric infrastructure failures in Nigeria: a survey-based analysis of the costs and adjustment responses', *Energy Policy* **31**(14), 1519–1530.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0301421502002082*

Alam, M. (2013), 'Coping with blackouts: Power outages and firm choices'.

Alby, P. and Dethier, J.-J. (2013), 'Firms Operating under Electricity Constraints in Developing Countries', *World Bank Economic Review* **27**(1), 109–132.
**URL:** *https://elibrary.worldbank.org/doi/abs/10.1093/wber/lhs018*

Allcott, H., Collard-Wexler, A. and O'Connell, S. D. (2016), 'How Do Electricity Shortages Affect Industry? Evidence from India', *American Economic Review* **106**(3), 587–624.
**URL:** *http://www.aeaweb.org/articles?id=10.1257/aer.20140389*

Anderson, T. W. and Rubin, H. (1949), 'Estimation of the Parameters of a Single Equation in a Complete System of Stochastic Equations', *The Annals of Mathematical Statistics* **20**(1), 46–63.
**URL:** *http://www.jstor.org/stable/2236803*

Angrist, J. D. and Pischke, J.-S. (2008), *Mostly harmless econometrics: An empiricist's companion*, Princeton university press.

Arnold, J. G., Srinivasan, R., Muttiah, R. S. and Williams, J. R. (1998), 'Large Area hydrologic modeling and assessement part 1: Model development', *JAWRA Journal of the American Water Resources Association* **34**(1), 73–89.
**URL:** *http://dx.doi.org/10.1111/j.1752-1688.1998.tb05961.x*

Baisa, B., Davis, L. W., Salant, S. W. and Wilcox, W. (2010), 'The welfare costs of unreliable water service', *Journal of Development Economics* **92**(1), 1–12.

Baum, C., Schaffer, M. and Stillman, S. (2010), *ivreg2: stata module for extended instrumental variables/2SLS, GMM and AC/HAC, LIML and k-class regression*.
**URL:** *https://ideas.repec.org/c/boc/bocode/s425401.html#cites*

Calderón, C. and Servén, L. (2004), *The Effects of Infrastructure Development on Growth and Income Distribution*, Policy Research Working Papers, The World Bank.
**URL:** *https://doi.org/10.1596/1813-9450-3400*

Canning, D. and Pedroni, P. (2008), 'Infrastructure, long-run economic growth and causality tests for cointegrated panels', *The Manchester School* **76**(5), 504–527.
**URL:** *http://dx.doi.org/10.1111/j.1467-9957.2008.01073.x*

Carranza, E. and Meeks, R. (2016), *Shedding Light: Understanding Energy Efficiency and Electricity Reliability*, Policy Research Working Papers, The World Bank.
**URL:** *https://doi.org/10.1596/1813-9450-7891*

Cattelaens, P., Limbacher, E.-L., Reinke, F., Stegmueller, F. F. and Brohm, R. (2015), Overview of the Vietnamese Power Market – A Renewable Energy Perspective, Report, GIZ Viet Nam Energy Support Programme.

Cole, M. A., Elliott, R. J., Occhiali, G. and Strobl, E. (2018), 'Power outages and firm performance in sub-saharan africa', *Journal of Development Economics* **134**, 150 – 159.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0304387818305054*

Danish Energy Agency (2017), Vietnam Energy Outlook Report 2017, Report, Danish Energy Agency.

Davis, J., Kang, A., Vincent, J. and Whittington, D. (2001), 'How Important is Improved Water Infrastructure to Microenterprises? Evidence from Uganda', *World Development* **29**(10), 1753–1767.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0305750X01000596*

De Loecker, J. (2011), 'Product Differentiation, Multiproduct Firms, and Estimating the Impact of Trade Liberalization on Productivity', *Econometrica* **79**(5), 1407–1451.
**URL:** *http://dx.doi.org/10.3982/ECTA7617*

Doe, F. and Asamoah, E. S. (2014), 'The Effect of Electric Power Fluctuations on the Profitability and Competitiveness of SMEs: A Study of SMEs within the Accra Business District of Ghana', *Journal of Competitiveness* **6**(3), 32–48.

Duflo, E. and Pande, R. (2007), 'Dams*', *The Quarterly Journal of Economics* **122**(2), 601–646.
**URL:** *http://dx.doi.org/10.1162/qjec.122.2.601*

EAU-WB (2017), Firm Level Productivity Estimates: Methodological Note, Report, Enterprise Analysis Unit - World Bank.

Esfahani, H. S. and Ramırez, M. T. (2003), 'Institutions, infrastructure, and economic growth', *Journal of Development Economics* **70**(2), 443–477.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0304387802001050*

EVN (2015*a*), EVN Profile 2014-2015, Report, Electricity of Vietnam.
**URL:** *http://www.evn.com.vn/d6/gioi-thieu-d/Thong-tin-EVN-2014-2015-2-50-16794.aspx*

EVN (2015*b*), Report on National Power System Operation 2014, Report, Electricity of Vietnam.

EVN (2017), Vietnam Electricity Annual Report 2016, Report, Electricity of Vietnam.
**URL:** *http://www.evn.com.vn/d6/news/Bao-cao-thuong-nien-EVN-2016-2-50-19547.aspx*

FAO (2007), 'Digital Soil Map of the World'.
**URL:** *http://www.fao.org/geonetwork/srv/en/metadata.show?id=14116*

FAO (2015), 'GAUL 2015 Data License'.

Fisher-Vanden, K., Mansur, E. T. and Wang, Q. (2015), 'Electricity shortages and firm productivity: Evidence from China's industrial firms', *Journal of Development Economics* **114**, 172–188.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0304387815000048*

Gassman, P. W., Sadeghi, A. M. and Srinivasan, R. (2014), 'Applications of the SWAT Model Special Section: Overview and Insights', *J Environ Qual* **43**(1), 1–8.
**URL:** *http://www.ncbi.nlm.nih.gov/pubmed/25602534*

Grainger, C. A. and Zhang, F. (2017), The impact of electricity shortages on firm productivity : evidence from Pakistan, Report, World Bank Group.
**URL:** *http://documents.worldbank.org/curated/en/978661498756334535/The-impact-of-electricity-shortages-on-firm-productivity-evidence-from-Pakistan*

Ha-Minh, D. and Nguyen, H. S. (2017), 'Is electricity a ordable and reliable for all in Vietnam'.
**URL:** *https://hal-enpc.archives-ouvertes.fr/hal-01389981v3*

Hansen, M., DeFries, R., Townshend, J. and Sohlberg, R. (1998), 'UMD Global Land Cover Classification, 1 Kilometer'.

Hansen, M., DeFries, R., Townshend, J. and Sohlberg, R. (2000), 'Global land cover classification at 1km resolution using a decision tree classifier', *International Journal of Remote Sensing* **21**, 1331–1365.

Holl, A. (2004), 'Manufacturing location and impacts of road transport infrastructure: empirical evidence from Spain', *Regional Science and Urban Economics* **34**(3), 341–363.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0166046203000590*

Hussain, Z., u Salam, M. H., Shah, S. M., Shah, R. H., Memon, N. A., Memon, M. and Kha, R. A. (2018), 'Technical losses ratio: Analysis of electric power transmission and distribution network', *International Journal of Computer Science and Network Security* **18**, 131–136.
**URL:** *http://paper.ijcsns.org/07*$_book/201809/20180917.pdf$

IEEE Working Group on Distribution Reliability (2015), 'IEEE Benchmark Year 2015: Results for 2014 Data'.
**URL:** *http://grouper.ieee.org/groups/td/dist/sd/doc/Benchmarking-Results-2014.pdf*

Iimi, A. (2011), 'Effects of improving infrastructure quality on business costs: Evidence from firm-level data in Eastern Europe and Central Asia', *The Developing Economies* **49**(2), 121–147.
**URL:** *http://dx.doi.org/10.1111/j.1746-1049.2011.00126.x*

Katayama, H., Lu, S. and Tybout, J. R. (2009), 'Firm-level productivity studies: Illusions and a solution', *International Journal of Industrial Organization* **27**(3), 403–413.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0167718708001197*

Kaur, S. (2014), 'Nominal Wage Rigidity in Village Labor Markets', *National Bureau of Economic Research Working Paper Series* **No. 20770**.
**URL:** *http://www.nber.org/papers/w20770*

Kleibergen, F. and Paap, R. (2006), 'Generalized reduced rank tests using the singular value decomposition', *Journal of Econometrics* **133**(1), 97–126.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0304407605000850*

Kleibergen, F. and Schaffer, M. (2007), *RANKTEST: Stata module to test the rank of a matrix using the Kleibergen-Paap rk statistic*.

Lee, K. S., Anas, A. and Oh, G.-T. (1999), 'Costs of Infrastructure Deficiencies for Manufacturing in Nigerian, Indonesian and Thai Cities', *Urban Studies* **36**(12), 2135–2149.
**URL:** *http://www.jstor.org/stable/43084411*

Lehner, B. and Grill, G. (2013), 'Global river hydrography and network routing: baseline data and new approaches to study the world's large river systems', *Hydrological Processes* **27**(15), 2171–2186.
**URL:** *http://dx.doi.org/10.1002/hyp.9740*

Lehner, B., Verdin, K. and Jarvis, A. (2008), '"New Global Hydrography Derived From Spaceborne Elevation Data"', *Eos, Transactions American Geophysical Union* **89**(10), 93–94.
**URL:** *http://dx.doi.org/10.1029/2008EO100001*

Levinsohn, J. and Petrin, A. (2003), 'Estimating Production Functions Using Inputs to Control for Unobservables', *The Review of Economic Studies* **70**(2), 317–341.
**URL:** *http://www.jstor.org/stable/3648636*

Li, J. and Heap, A. D. (2008), 'A Review of Spatial Interpolation Methods for Environmental Scientists', *Geoscience Australia* **Record 2008/23**.

Marschak, J. and Andrews, W. H. (1944), 'Random Simultaneous Equations and the Theory of Production', *Econometrica* **12**(3/4), 143–205.
**URL:** *http://www.jstor.org/stable/1905432*

Matsuura, K. and Willmott, C. J. (2009), 'README: Terrestrial Precipitation: 1900-2014 Gridded Monthly Time Series Version 4.01 '.
**URL:** *http://climate.geog.udel.edu/~climate/html_pages/Global2_Clim/README.global2_clim.html*

Maureen, D. A. and Jean, P. P. (2000), 'GIS-based construction of baseline climatologies for the Mediterranean using terrain variables', *Climate Research* **14**(2), 115–127.
**URL:** *http://www.int-res.com/abstracts/cr/v14/n2/p115-127/*

McRae, S. (2015), 'Infrastructure Quality and the Subsidy Trap', *American Economic Review* **105**(1), 35–66.
**URL:** *http://www.aeaweb.org/articles?id=10.1257/aer.20110572*

Mensah, J. T. (2016), Bring Back Our Light: Power Outages and Industrial Performance in Sub-Saharan Africa, Report.

Min, B. and Gaba, K. (2014), 'Tracking Electrification in Vietnam Using Nighttime Lights', *Remote Sensing* **6**(10), 9511.
**URL:** *http://www.mdpi.com/2072-4292/6/10/9511*

MONRE (2012), Report on National Environment 2012, Report, Ministry of Natural Resources and Environment.

Nalder, I. A. and Wein, R. W. (1998), 'Spatial interpolation of climatic Normals: test of a new method in the Canadian boreal forest', *Agricultural and Forest Meteorology* **92**, 211–215.

Neitsch, S., Arnold, J., Kiniry, J. and Williams, J. (2009), 'Soil and Water Assessment Tool Theoretical Documentation Version 2009'.

Nguyen-Tien, V., Elliott, R. J. R. and Strobl, E. A. (2018), 'Hydropower generation, flood control and dam cascades: A national assessment for Vietnam', *Journal of Hydrology* **560**, 109–126.
**URL:** *https://www.sciencedirect.com/science/article/pii/S0022169418301458*

Olley, G. S. and Pakes, A. (1996), 'The Dynamics of Productivity in the Telecommunications Equipment Industry', *Econometrica* **64**(6), 1263–1297.
**URL:** *http://www.jstor.org/stable/2171831*

Pavcnik, N. (2002), 'Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants', *The Review of Economic Studies* **69**(1), 245–276.
**URL:** *http://www.jstor.org/stable/2695960*

Picard, R. (2017), *GEODIST: Stata module to compute geodetic distances*.

Reinikka, R. and Svensson, J. (2002), 'Coping with poor public capital', *Journal of Development Economics* **69**(1), 51–69.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0304387802000524*

Saha, S., Moorthi, S., Pan, H.-L., Wu, X., Wang, J., Nadiga, S., Tripp, P., Kistler, R., Woollen, J., Behringer, D., Liu, H., Stokes, D., Grumbine, R., Gayno, G., Wang, J., Hou, Y.-T., Chuang, H.-Y., Juang, H.-M. H., Sela, J., Iredell, M., Treadon, R., Kleist, D., Van Delst, P., Keyser, D., Derber, J., Ek, M., Meng, J., Wei, H., Yang, R., Lord, S., Van Den Dool, H., Kumar, A., Wang, W., Long, C., Chelliah, M., Xue, Y., Huang, B., Schemm, J.-K., Ebisuzaki, W., Lin, R., Xie, P., Chen, M., Zhou, S., Higgins, W., Zou, C.-Z., Liu, Q., Chen, Y., Han, Y., Cucurull, L., Reynolds, R. W., Rutledge, G. and Goldberg, M. (2010), '"The NCEP Climate Forecast System Reanalysis"', *Bulletin of the American Meteorological Society* **91**(8), 1015–1057.

Saha, S., Moorthi, S., Wu, X., Wang, J., Nadiga, S., Tripp, P., Behringer, D., Hou, Y.-T., Chuang, H.-y., Iredell, M., Ek, M., Meng, J., Yang, R., Mendez, M. P., van den Dool, H., Zhang, Q., Wang, W., Chen, M. and Becker, E. (2014), 'The NCEP Climate Forecast System Version 2', *Journal of Climate* **27**(6), 2185–2208.

Sanderson, E. and Windmeijer, F. (2016), 'A weak instrument F-test in linear IV models with multiple endogenous variables', *Journal of Econometrics* **190**(2), 212–221.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0304407615001736*

Sarsons, H. (2015), 'Rainfall and conflict: A cautionary tale', *Journal of Development Economics* **115**, 62–72.

Simoes, A. J. G. and Hidalgo, C. A. (2011), The economic complexity observatory: An analytical tool for understanding the dynamics of economic development, *in* 'Workshops at the twenty-fifth AAAI conference on artificial intelligence'.

Solow, R. M. (1957), 'Technical Change and the Aggregate Production Function', *The Review of Economics and Statistics* **39**(3), 312–320.
**URL:** *http://www.jstor.org/stable/1926047*

Son, P. T. and Voropai, N. (2015), The Major Outage in South Vietnam in 2013: The Nature of Blackout, Security Measures and Strategy of National Power System Modernization, *in* N. I. Voropai, ed., 'Joint 6th Conference of International Institute for Critical Infrastructures and 6th International Conference on Liberalization and Modernization of Power Systems', Saint Petersburg.

Stahl, K., Moore, R. D., Floyer, J. A., Asplin, M. G. and McKendry, I. G. (2006), 'Comparison of approaches for spatial interpolation of daily air temperature in a large region with complex topography and highly variable station density', *Agricultural and Forest Meteorology* **139**(3-4), 224–236.

Staiger, D. and Stock, J. H. (1997), 'Instrumental Variables Regression with Weak Instruments', *Econometrica* **65**(3), 557–586.
**URL:** *http://www.jstor.org/stable/2171753*

Steinbuks, J. (2011), Financial Constraints and Firms' Investment: Results from a Natural Experiment Using Power Interruption, Report.

Stock, J. H. and Yogo, M. (2005), *Testing for Weak Instruments in Linear IV Regression*, Cambridge University Press, Cambridge, pp. 80–108.
**URL:** *https://www.cambridge.org/core/books/identification-and-inference-for-econometric-models/testing-for-weak-instruments-in-linear-iv-regression/8AD94FF2EFD214D05D75EE35015021E4*

UNDP (2010), Vietnam's Infrastructure Constraints, Report, United Nations Development Programme in Vietnam.

Vagliasindi, M. and Besant-Jones, J. (2013), *Power Market Structure Revisiting Policy Options*, Directions in Development - Energy and Mining, The World Bank, Washington, D.C.

Van Beveren, I. (2012), 'Total factor productivity estimation: A practical review', *Journal of Economic Surveys* **26**(1), 98–128.
**URL:** *http://dx.doi.org/10.1111/j.1467-6419.2010.00631.x*

Vincenty, T. (1975), 'Direct and inverse solutions of geodesics on the ellipsoid with application of nested equations', *Survey Review* **23**(176), 88–93.
**URL:** *http://dx.doi.org/10.1179/sre.1975.23.176.88*

WB (2017), 'Vietnam electricity transmission network'.
**URL:** *https://energydata.info/dataset/vietnam-electricity-transmission-network/resource/2f577059-d5dc-447e-8dda-45fa6c1fbca9?inner_span=True*

WB and MPI (2016), Vietnam 2035 : Toward Prosperity, Creativity, Equity, and Democracy, Report, World Bank (WB) and Vietnam Misnistry of Planning and Investment (MPI).
**URL:** *http://documents.worldbank.org/curated/en/996421479825859721/pdf/103435-v2-PUBLIC.pdf*

Wooldridge, J. M. (1999), 'Asymptotic Properties of Weighted M-estimators for variable probability samples', *Econometrica* **67**(6), 1385–1406.
**URL:** *http://dx.doi.org/10.1111/1468-0262.00083*

Wooldridge, J. M. (2001), 'Asymptotic properties of weighted M-estimators for standard stratified samples', *Econometric Theory* **17**(2), 451–470.
**URL:** *https://www.scopus.com/inward/record.uri?eid=2-s2.0-0035627805&partnerID=40&md5=98e1c4c6b27aaf51368fa47e601964aa*

Wooldridge, J. M. (2009), 'On estimating firm-level production functions using proxy variables to control for unobservables', *Economics Letters* **104**(3), 112–114.
**URL:** *http://www.sciencedirect.com/science/article/pii/S0165176509001487*

Wooldridge, J. M. (2010), *Econometric analysis of cross section and panel data*, 2 edn, The MIT PRess, Cambridge, Massachusetts, London, England.

# Chapter 3

# Do Natural Disasters Make Politicians More Environmentally Friendly? - Evidence from Environmental Legislation in the US Senate

## Chapter abstract

This paper investigates whether United States Senators are more likely to vote in favour of environmentally friendly legislation following a natural disaster. To this end we combine senatorial scores of roll call votes on environmental legislation with modelled state level human and economic natural disaster losses over a 44 year period. Our empirical results show that support for environmental legislation increases in response to human losses but falls after economic damages. We find the documented response to such events is two years, although senators from states with low natural disaster risk, high income, or those that benefit from statewide Presidential Disaster Declarations, vote for more environmentally friendly legislation within a year. Regardless, the impact is short-lived.

"Disasters are very political events."

*A testimony to senators by James L. Witt, the former director of FEMA (April 1996)*

"We can't destroy the competitiveness of our factories in order to prepare for nonexistent global warming. China is thrilled with us."

*A tweet of Senator Donald J. Trump (November 2012)*

"I don't think that's changed,"

*A response from White House Press Secretary when asked whether Hurricanes Irma and Harvey altered the view of President Donald J. Trump on climate change (September 2017)*

## 3.1 Introduction

Following the inauguration of President Donald Trump, there have been a number of changes in US environmental policies, including the introduction of the fossil-fuel-reviving 'America First Energy Plan', a threat to withdraw the US from the Paris Climate Change Agreement, and the removal of such terms as 'climate change' or 'global warming' from official government documents, plans, and strategies (Wolff, 2017; Mckibben, 2017; Flavelle, 2018). Coincidentally, shortly after the inauguration of the president in 2017, the US was faced with a series of large natural disasters with economic damages estimated to be $306 billion dollars. Specifically, the cost of 16 single events exceeded 1 billion dollars, including 3 of the 5 costliest hurricanes have hit the US since 1900 (Mooney and Dennis, 2018; NOAA National Hurricane Center, 2018).[1]

[1]The three hurricanes were Harvey ($125 billion), Irma ($25 billion), and Maria ($90 billion).

Following these disasters, scientists, and environmental advocates argues that the government should reconsider the current environmentally hostile of the US' environmental policy (Friedman, 2017; Colman, 2017, 2018). However, despite these protestations, there is little progress has been made. In this paper we investigate whether extreme losses caused by natural disasters influenced politician's voting behaviour on the environmental legislation. More specifically, we investigate whether senator's preference for environment changed after their constituencies were severely hit by natural disasters.

There are several reasons why one may expect natural disasters to alter Senate level legislation in general, and in particular those associated with the environment. While ideology has been found to play an important role in congressional voting in the US (Poole and Rosenthal, 1985; Arnold, 1990; Lee *et al.*, 2004; Ringquist and Dasse, 2004; Clinton, 2006; Poole and Rosenthal, 2007), one would expect that legislators, who are elected to act on behalf of their electorates, take into account the preferences of their constituencies when casting their votes (Anderson and Mizak, 2006; Tanger *et al.*, 2011; Chupp, 2011; Canes-Wrone *et al.*, 2011; Miler, 2016; Vandeweerdt *et al.*, 2016). In this regard, natural disasters, which are unanticipated and can have a devastating impact on local communities, could serve as 'focusing' events, in that they can grab the public's attention, result in extensive media coverage, and trigger public debate, thus possibly changing the balance of competing advocate groups, and in turn altering the attitude and actions of elected legislators (Kahn, 2007; Birkland, 2016).[2] There are at least two different narratives that can arise in the aftermath of a natural disaster. First, perception of the close relationship between natural disasters and the environment means that issues related

[2] Boscarino (2009) explains this phenomenon as 'problem surfing', that is advocacy groups tend to attach any seemingly relevant problems that arise in society to the preferred solution that they are keen on fighting for. For example, in his empirical work he finds that two sustainable forestry advocacy groups, Wilderness Society and Sierra Club, take advantage of different salient events covered by media belonging to 5 different topics: wildlife, water quality, recreation, economic inefficient and climate change to promote their campaign.

to the environment may emerge as a critical issue in the constituencies that have been impacted by a natural disaster. One common argument is that environmental degradation such as changes to the underlying climate makes natural hazards more damaging and/or frequent and hence increases the vulnerability of affected communities (UNEP, 2007; Gupta and Nair, 2012; Wouter Botzen and Van Den Bergh, 2012; Estrada *et al.*, 2015) and legislation is expected to respond to such a concern. For example, after the catastrophic hurricane Katrina, many environmentally friendly bills were proposed to cope with the risks of climate change. At the same time, natural disasters can directly or indirectly result in further deterioration of the environment, for example ecosystem destruction, oil spills, and contaminant mobilisation (Labadie, 2006; Atkin, 2017; Dart *et al.*, 2018; Natter and Calkins, 2018). Therefore, natural disasters could help trigger demand for stringency of environmental regulation. For example, the concern on the risk of earthquake contributed to the introduction of Gravel amendment (1971) to the Atomic Energy Commission Authorizations (HR 9388), which aimed to delay nuclear testing in Alaska.[3]

On the other hand, natural disasters can cause considerable economic losses, that means constituencies prioritise economic recovery and redevelopment.[4] Therefore, environmental regulations, if they are believed to impose additional costs on businesses and negatively impact employment, even if it is just in the short term, could become less preferable where costly natural disasters strike. An example for the thinking that environmental protection should step out in emergency is the proposal by Senator Rand Paul (2012), which sought to amend the Moving Ahead for Progress in the 21st Century Act (MAP-21) (S. 1813), and relax environmental

[3] See http://scorecard.lcv.org/roll-call-vote/1971-138-nuclear-testing

[4] While it has been estimated that about one third of the working population in the US believe in the trade-off between environmental regulation and jobs (Goodstein, 1994), existing studies suggest just negligible impacts of environmental regulation on productivity and employment in the US (Ferris *et al.*, 2017). There is a popular political mythology that exaggerates the scopes, intensity and duration of such impacts on firms, industries, and localities (Meyer, 2002). Also, an analysis by Kahn and Kotchen (2010) found that increased unemployment rate and decreased income reduce public concern on environment.

regulations for the rebuilding of transportation project after disasters.[5]

In order to study how natural disasters affect congressmen voting on environment related laws, we put together a 44 year data set of the 'environmentally friendly' voting behaviour of US Senators and state level measures of human and economic losses caused by different types of natural disasters. To measure environmental senatorial voting since 1971 we use the scores constructed by the League of Conservation Voters (2018) from records of selected roll call votes at the Senate. A naïve approach is just directly using the level of disaster damages in modelling, which implicitly assumes a uniformly linear impact on voting at the congress of natural damages of different magnitudes and ignores various degrees of exposure to natural disaster across different states. As it has been highlighted in the literature, only salient events have noticeable political power and therefore a challenge in building measures of state level natural disaster losses is to identify events that are important, i.e., rare, enough to possibly trigger changes in attitude, and to take account of the likelihood that the definition of 'rare' may differ across states given their historical exposure to natural disasters. To model these features we use the comprehensive record of monetary and non-monetary losses due to natural events contained in the SHELDUS database (Hazards & Vulnerability Research Institute, 2015) and identify the more extreme natural disasters using extreme value theory (EVT). Arguably, EVT is ideally suited to the task at hand, as it allows one to take account of the 'fat tail' distribution that are typical of losses due to natural events, where there are many smaller, negligible, and a few potentially very damaging events (the 'fat tails'). To isolate and classify the probabilities of the latter we employ a peak over threshold (POT) model for each state, thus allowing the associated derived probabilities of events to differ across space.

[5]See details at http://scorecard.lcv.org/roll-call-vote/2012-47-environmental-review-transportation-rebuilding.

Our study contributes to a strand of the literature that investigates political consequences of natural disasters, and more specifically within the context of the US. A majority of these studies examines the executive branch and how voters punish or reward federal and local governments after the occurrence of a natural disaster (Abney and Hill, 1966; Achen and Bartels, 2004; Malhotra and Kuo, 2008; Healy and Malhotra, 2009; Gasper and Reeves, 2011; Bechtel and Hainmueller, 2011). Several studies also look at the legislative branch, paying attention to the policy domains of disaster relief and prevention (Birkland, 1996, 2016).

To the best of our knowledge, there has been no empirical study on the impact of natural disasters within the broader domain of environmental legislation. Arguably, a challenge in using findings from the existing studies to infer the political impacts of natural disasters has been external validity. More specifically, most of the literature has focused on one or a few salient events, such as a 500-year flood, and thus it is difficult to generalise from or directly compare their findings to other contexts where the 'rarity' of the event may be very different. In addition, the restriction to specific types of disasters (for example hurricanes only) fails to take account of the fact that many, particularly, climatic events are driven by similar forces, such as the El Niño–Southern Oscillation (Goddard and Dilley, 2005), and thus that it may be the cumulative losses due to natural disasters that matter in terms of changing environmental attitudes. The approach we take in this paper allows us to homogenise the rarity of all economic and human losses across time and states. The key identification assumption is that whenever the yearly accumulated damage from natural disasters in a constituency exceeds an *arbitrary* degree of rarity, it may become a matter of public concern and influence the behaviour of elected politicians (senators). Otherwise, it will be considered non-salient and likely to be ignored. The empirical threshold we use in this study is 10-year return level, although we investigate whether alternative thresholds are more appropriate.[6]

To briefly summarise our results, we find that the environmental voting patterns of senators are responsive to extreme losses from natural disasters in their constituencies. However, this response is not instantaneous, in that a significant signal is found on average two years after an event and lasts only a year. Importantly, human loss shocks and economic loss shocks from the disasters have opposite effects. The former makes the senators lean toward 'green' policies, while the latter drives them away. State characteristics, such as low exposure to natural disasters, high personal income, and benefiting from Presidential Disaster Declarations make the responses of senators earlier and stronger.

The remainder of the paper is organised as follows. Section 2 describes our data sets and construction of variables. Section 3 presents our regression specification, the results of which are shown and discussed in Section 4. In Section 5 we conduct some counter-factual analysis. Finally, Section 6 concludes.

## 3.2 Data

### 3.2.1 Senatorial Environmental Voting Scores

To construct an indicator of environmental friendly voting of Senators we use the National Environmental Scorecard by League of Conservation Voters (2018) (LCV). More precisely, every year since the first Earth Day (1970), LCV has consulted experts from over 20 organisations

[6] The threshold 10-year return level should not be mistakenly interpreted as an extreme level that is repeatedly exceeded each decade but rather an extreme level that could be exceeded every year with a chance of 1/10= 10%

that have a reputation for supporting environmental conservation to select a list of key votes in environment-related issues to construct the LCV scores. Accordingly, each vote is scored 1 (pro-environment) if in line with LCV's position, or 0 (anti-environment) otherwise, including absentee votes. The annual score for each legislator, except for those who were ill or died, and the Speakers of the House, whose vote is discretionary, is computed as the average score of all selected issues within the year and then transformed into a scale from 0 (environment enemies) to 100 (environment heroes). In certain years, some important issues are counted twice while the sponsorship of some bills or petitions may be selected as replacements for real votes to construct the scores. In order to control for changes in issues of legislative pieces each year, we construct their share as grouped by: (1) Air issues, (2) Clean Energy issues, (3) Dirty Energy/Toxics/Public Right to Know issues, (4) Water, Oceans and Drilling issues, (5) Lands/Forest/Wildlife issues, (6) Transportation issues, (7) Climate change issues, and (8) Other issues.[7]

### 3.2.2 Senatorial Characteristics

To control for senators' characteristics we use information from Voteview (Lewis *et al.*, 2017) and the Congress Legislator project on GitHub.[8] The Voteview dataset provides information about the birth date, party affiliation, and ideology of the congressmen.[9] As an ideology control, we include the two dimensions of NOMINATE, which are calculated from DW-NOMINATE

[7]Note that the sum of these shares could exceed 100 as a vote can belong to multiple groups. In addition these share variables are not absorbed by year fixed effects as they can vary over legislators each year if some, for certain reasons (such as midterm election, illness, death...) , cast fewer votes in the selected issues.

[8]The Voteview data set collates information on US congressmen, president and vice president from 1789 to recent, using various information sources; see https://github.com/unitedstates/congress-legislators for details.

[9]Party affiliation of legislators in the LCV dataset is corrected for those senators who switched party or changed jobs.

(Dynamic Weighted NOMINATE Three-step Estimation) (Poole, 2005; Poole and Rosenthal, 2007). The first dimension captures ideology in terms of economic/re-distributive issues, while the second accounts for social/racial issues. For both dimensions, which are normalised between -1 and 1, a higher estimate means a more conservative politician. The estimates are changed for those that switched party. The GitHub data set also provides information on the gender and class of the senators (to determine the election year) and the history of their appointment at the Senate.[10]

### 3.2.3 Natural Disasters

To measure the impact of natural disasters we rely on the SHELDUS™ database (Hazards & Vulnerability Research Institute, 2015). The database tracks the damages of natural hazards and perils including, but not limited to, thunderstorms, hurricanes, floods, wildfires, tornadoes, flash floods, and heavy rainfalls.[11] Annual losses are given in terms of crop losses, properties losses, injuries, and fatalities. We have access to data at the county level for the period 1960 - 2014. Since senators are elected by their states as a whole, we aggregate losses to the state level. We compute human losses at state level as the sum of annual injuries and fatalities and economic losses as the aggregated damage to crops and properties by year. We adjust values of the later by 2014 prices to cancel out the possible impact of inflation. In addition, we look at the intensity of losses (per capita variables) rather than their levels to take into account the changes in population and economic density.

[10] The tenure of senators is 6 years. Every 2 (even numbered) years, one-third of their seats (33-34) are re-elected and the class helps determine the year of election. For example, those of Class 1, 2, and 3 are up for re-election in 2018, 2020 and 2022, respectively.

[11] In full, SHELDUS™ includes 18 types of natural hazards: Avalanche, Coastal, Drought, Earthquake, Flood, Fog, Hail, Heat, Hurricane/Tropical Storm, Landslide, Lightning, Severe Thunderstorm, Tornado, Tsunami/Seiche, Volcano, Wildfire, Wind, Winter Weather

To identify the salient, i.e., relatively rare, human and economic loss years in a state we use to extreme values theory (EVT) and employ a Peak Over a Threshold model (POT) (Coles, 2001). The approach can be summarised as follows. If, for each of the 50 states, for each of the two series of annual losses, we assume that they are a sequence of independently and identically random variables, then an appropriate normalisation of the maximum of such a sequence, according to the Extremal Types Theorem (Fisher and Tippett, 1928), must asymptotically approximate one of 3 extreme value distribution families, namely Fréche, Gumbel, or Weilbull, which can be generalized by a Generalised Extreme Value (GEV) distribution (Jenkinson, 1955). Under certain asymptotic arguments, the probabilities of the extremes of these sequences, above a certain threshold, can then be modelled via generalised Pareto distribution (GPD); see (Pickands, 1975). Importantly, for the practical implementation of POTs is the choice of the extremes' threshold. A high threshold limits the number of observations, making the estimation less precise, while a low threshold undermines the underlying asymptotic assumptions, posing a potential risk of bias in the estimation. We follow the guidelines of Coles (2001) when use a series of visualisation tools determining the threshold for each series. First, we draw the mean residual life plot (MRL), which captures the relationship between the average exceedances and thresholds, and select a low threshold where such a relationship still plausibly mirrors a straight line, as would be expected from the theory. The selection is verified by a POT parameter stability plot.[12] After the threshold is chosen, the GPD is estimated by the Maximum Likelihood Estimator (MLE). Post-estimation graphs are used to further assess the selection of threshold. Appendix 3.A provides a detailed explanation of our EVT and POT approach.

The estimated GDP distribution is used to determine the return level $z(N)$ of the extreme

[12] As suggested by the theory, once the threshold is appropriate, relevant (transformed) parameters must be stable when increase the value of threshold (see Appendix 3.A for details)

loss intensity values corresponding to a predefined return period of $N$ years. For our baseline results we choose a return period of 10 years, which corresponds to a return level $z(10)$ such that the annual natural disaster damages/losses in a given state in any year can exceeds such a level with a probability of $1/10 = 0.1$.

### 3.2.4 Other State Level Controls

In our estimations we also control for a number of state characteristics including demographic, economic, and weather related, that could be correlated with voting behaviour and the possibility that natural events translate into large losses. In terms of demographic data we take information from ‘The US Population Data by National Cancer Institute’, which provides an estimate of the annual population by age, sex, and race at the county level.[13] To generate controls for the macro-economic environment (GDP, personal income, and implicit price deflator) at the state level, we use data from Bureau of Regional Economic Analysis (BEA).[14]

As noted by Auffhammer *et al.* (2013), when modeling climate related phenomina it is important to also control for general weather patterns that could be correlated. To construct measure at state level temperature and precipitation we use data from the nClimDiv (NOAA, 2014; Vose *et al.*, 2014) that interpolates climatic data from stations at 5km × 5km resolution using an area weighting method and taking into account topographic and network variability. The data covers states in the contiguous United States (CONUS) and Alaska (added in 2015, based on 1971-2000 PRISM averages) and excludes Hawaii. For Hawaii, we use the Global

[13] The data is accessible at https://seer.cancer.gov/popdata/methods.html.
[14] Data is available at https://www.bea.gov/regional/downloadzip.cfm.

Summary of the Year data provided by National Climatic Data Center (NCDC).[15]

### 3.2.5 Summary Statistics

Table 3.1 summarises the data used in our regression. After the data matching processes, we obtain 4,414 observations from 381 senators that we were able to obtain the full set of senatorial environmental voting scores, natural disaster measures, senatorial characteristics and other state-level controls.[16] Regarding our variables of interest (the modelled natural disaster measures), we depict the spatial distribution of human and economic losses in Figures 3.1 and 3.2, respectively. As can be seen from the figures, the 10-year return levels for economic loss intensity in 2014 prices ranges from 16.5 (Connecticut) to 509.2 (Iowa) dollars per head, while the 10-years return levels for human loss intensity ranges from 4.7 (Rhode Island) to 144.2 (Mississippi) deaths and injuries per million of the population. Spatially, the South, followed by the Midwest, has the highest 10-year return levels of ND damages, both in terms of economic and, human losses. In Figure 3.3 we shows the temporal variation of human and economic losses in conjunction with the number of states affected. As can be seen there has been considerable variation in both the incidence and the intensity.

**[Table 3.1 about here]**

**[Figure 3.1, 3.2, and 3.3 about here]**

[15] More specifically, we compute temperature and precipitation for Hawaii as the average of data from three stations Hilo International Airport, Honolulu observatory, and Lihue weather service office airport.

[16] The average age of Senator is quite high, at 58.6. The oldest senator in the dataset is Sen Strom Thurmond (1902), who was 100 years old when serving the Senate in 2002 before his death in 2003. The women are underrepresented in the Senate, with an average share of only 7.3% over the entire period. The share was almost negligible in the early years, then dramatically rose since 1992 and reached nearly 20% in 2014.

## 3.3 Specification

Our benchmark specification to estimate whether natural disaster shocks have an impact on environmental voting patterns of senators is given by:

$$Y_{ijt} = \alpha + \sum_{k=0}^{q} \beta_k Hshock_{jt-k} + \sum_{k=0}^{q} \gamma_k Eshock_{jt-k} + \Psi X_{it} + \Omega Z_{jt} + \mu_i + \nu_t + \varepsilon_{ijt} \tag{3.1}$$

where $Y_{ijt}$ is the average LCV in year $t$ of Senator $i$ elected to state $j$. $Hshock_{jt-k}$ is the human losses, a binary variable that indicates whether there were human losses due to natural disasters (per capita) in state $j$, $k$ years prior to year $t$ that exceeded the 10-year return level, and the binary variable $Eshock_{jt-k}$ for economic losses is similarly defined. We control for a delayed effect between the natural disasters and voting behaviour by including lagged values of $Hshock_{jt-k}$ and $Eshock_{jt-k}$. The sets of coefficients $\beta_k$ and $\gamma_k$ are the parameters of interest. $X_{it}$ is our set of variables that control for characteristics of senators including ideology (measured by 2-dimensions of the NOMINATE estimates), party affiliation, age, gender, tenure of legislators (whether they are in first year at the chamber and whether they are in an election year) and a range of issues (share of issues by topic) voted in year $t$. $Z_{jt}$ is a vector of state characteristics, including demography (share of voters by ethnicity and age), economy (average personal income, and real growth rate) and weather variables (precipitation, and temperature). The model also includes legislator ($\mu_i$), and time fixed effects ($\nu_t$). Time fixed effects control for common factors across the country that vary across years. Since senators represent states, legislator fixed effects control not only for time invariant unobserved senator heterogeneity, but also take account of state-specific time-invariant characteristics. Arguably, after controlling with for differences in local natural disaster loss exposure through these fixed effects, $Hshock_{jt-k}$ and

$Eshock_{jt-k}$ capture random, unanticipated realizations of the natural disaster loss distributions.[17] Standard errors are clustered at the state level in all specifications.

## 3.4 Results

### 3.4.1 Baseline regression

Table 3.2 shows the results from our baseline regressions. To this end we employ both an OLS [Ordinary Least Squares] (Columns 1-5) and a (senator) FE [Fixed Effects] (Column 6-10) model, where both include the same set of time varying control variables and year fixed effects. We also allow for up to four years of lagged values for our two main variables of interest. In a robustness check we also include lags of all control variables (see Section 3.4.2). Overall, our results show that natural disasters have a significant impact on voting patterns, although the effects depend on the time horizon examined. Importantly, the effect of the two types of shocks differ qualitatively, in that while relatively rare human loss events tend to induce legislators to vote for more environmentally friendly legislation, economic loss shocks have the opposite impact.

**[Table 3.2 about here].**

Comparing the two estimators, the OLS results tend to give larger coefficients. In our OLS results we find a significant impact for human losses for the year of the shock and up to 2 years

[17] Of course whether an environmental event translates into a natural disaster depends on time varying ex-ante population exposure, disaster mitigation policies and local infrastructure, all of which could feasibly also be correlated with voting patterns. We assume that these concerns are controlled for through our rich set of time varying state specific controls.

later with the largest coefficients for 2 years after the natural disasters. For economics losses, column (5) shows that the impact starts at $t-1$ and lasts until $t-2$, although the effect is sensitive to including other lags. In contrast, when we take into account senator and state heterogeneity in the FE model, the estimated coefficients tend to be lower, suggesting that a failure to control for these effects may induce an upward bias in the results. However impact for the 2-year lag remains significant at the 1% level for human loss shocks, and at the 10% level for the economic losses.

Since there appears to be no impact beyond two year lags for either natural disaster indicator, Column 8, which allows for up to a two year effect, is considered as our benchmark specification for our remainder of the paper. Accordingly, we can say that human losses in a particular state adds 2.66 points to a senatorial environment score 2 years after the event while an economic loss shock reduces it by 1.40 points. To put this in context, the average senatorial environmental score is 46.99 (N=4,414) for the whole sample, 23.52 for non-Democratic senators (N=2,123) and 68.75 for Democratic senators (N=2,291). One extension is to ask whether the impact of natural disasters remains significant if they simultaneously cause extreme losses in both monetary and human terms.[18] Under such circumstances, the total impact of natural disasters is the linear combination of both shocks. Using the benchmark specification, the combined coefficient for the 2 year lag variable is 1.26 with a standard error of 0.98.[19] The $t$-test cannot reject the null that such an overall effect is not statistically different from zero ($p$-value=0.197).[20]

[18]One should note that a feature of our ND shocks variables is that human loss shock and economic loss shock rarely occur together. More precisely, among our 2,200 state-year pairs (50 states $\times$ 44 years), there are 155 single human loss shocks, 192 single economic loss shocks, and 64 incidences of both occurring in the same year and state.

[19]As a numerical illustration, the benchmark specification can be explicitly written as $Y_{ijt} = \alpha + \sum_{k=0}^{2} \beta_k Hshock_{jt-k} + \sum_{k=0}^{2} \gamma_k Eshock_{jt-k} + \Psi X_{it} + \Omega Z_{jt} + \mu_i + \nu_t + \varepsilon_{ijt}$ and the combined coefficient at 2 year lags is $\beta_2 + \gamma_2$=2.66+(-1.40)=1.26.

[20]The coefficient, stand error, $t$ statistics and $p$-value of the combined effect here were computed by the STATA

Yet, when both damages happen together, the two significant impacts neutralise each other given the effects are in opposite directions and senators seem to be unresponsive to the the events that cause extreme losses to both human and the economy.

### 3.4.2 Robustness Tests

We conduct a number of robustness checks to gain further confidence in our findings. Firstly, in Table 3.3, we compare the findings of the benchmark specification (Column 1) with some alternative specifications (Columns 2 to 12). Odd numbered columns are variations on the benchmark specification and even numbered columns resemble the columns before but including up to 2 lags of all controls. Column (3) considers the impact of both types of natural disaster shock, but at $t-2$ only and excludes the shocks at $t-0$ and $t-1$. Column (5) only considers the impact of human loss shock and its lags. Column (7) only considers the impact of economic loss shock and its lags. Column (9) and (11) include dynamic terms of the dependent variable to address the concern that our benchmark specification fails to capture potential dynamics in environmental voting in our static model and that thus the lagged ND variables are partially picking these up. More precisely, we add to our baseline specification up to two lags of the LCV score, i.e., the same number of lags for which we find significant effects on economic and human losses, and re-estimate the model using both a FE (column 9) and Generalized Method of Moments [GMM] estimator (column 11), the latter of which takes account of the endogeneity of the lagged dependent variables. Accordingly, the significant impact of lagged human loss shock is robust across all specifications while the robustness of lagged economic loss shock varies. It becomes insignificant in Column 2, and 7-10 but turn to significant at 5% in Columns

command *lincom*.

9-10, where the dynamics of the dependent variable is added and estimated by GMM. Notably, in such a specification, the first lag of LCV score appears to be a significantly positive predictor of LCV score itself. A note of caution is that these 12 specifications are not always strictly comparable as the samples of some are slightly reduced when we try to include the lags of some variables that lack of historical observations.

**[Table 3.3 about here].**

As noted in the introduction, in the literature on the determinants of congressional voting ideology has been shown to be the one of the most important drivers. In parallel, it may affect the perceptions of natural disasters risk and the decide demand for adaptation measures (Botzen *et al.*, 2016). However, our proxy for ideology varies little after controlling for senator fixed effects (since it can only change due to a switch of party or a change to another political position), so that one may have some concerns over whether we might not by chance be capturing ideological changes concurrent with ND events. To further investigate this we replaced the NOMINATE measures by a more time-varying ideology proxy, namely Liberal Quotient (LQ) by American for Democratic Action (ADA). The LQ is a 'standard measure of political liberalism' (Americans for Democratic, 2017) and is constructed for each senator from the records of 20 selected votes each, which cover a wide range of issues, including domestic and international social and economic issues, as well as environmental concerns. Results of including this alternative ideology proxy, under the reduced sample size given that not all senators have observations for LQ, are illustrated in Table 3.4. Compared with baseline regressions in Table 3.2, the difference in coefficients is, however, negligible and the main conclusions remain.

**[Table 3.4 about here].**

After controlling for state level fixed effects, the ND losses are arguably unanticipated realisations of the ND loss distributions. A potential counter-argument is that the dependent variable (LCV score of elected senator) may serve as a proxy of local elite attitude and public opinion towards the environment in the associated state, which is possibly correlated with natural hazard prevention and preparedness and predicts the actual loss caused by natural disasters later. To shed a light on this issue, in Columns (6) to (10) of Table 3.5 we conduct a placebo test, where the treatment in the baseline (lags $t-1, ..., t-4$ of natural disaster shocks in Columns (6) to (10) of Table 3.2) is replaced by the leads $t+1, ..., t+4$ of these variables. One should note this will inevitably change our sample as we do not have natural disaster data after 2014. To make sure the results of our placebo test are not driven by sample variation, we replicate Columns (6) to (10) of Table 3.2 in Column (1) to (5) of Table 3.5 with the same restricted samples as the regressions with the lead variables. In this regard, although the point estimates of ND shock lags in these columns slightly differ from Table 3.2 the main conclusion is unchanged: senators react strongly to ND shocks at 2 years after the event. The results of the placebo test in Columns (6) to (10) of Table 3.2 indicate that there is almost no correlation between future ND shocks and senators' voting, except for the third lead of human loss shocks, although this is only at the 10% level. Thus, we can confidently rule out the reverse causality that environmental voting process predicts ND shocks.

**[Table 3.5 about here].**

To ensure that our significant results are not due to a chance occurrence of ND shocks and changes in environmental voting we also undertook a randomization (Monte Carlo permutation) test. More precisely, within each state ND shocks were randomly assigned to a year with a probability of 10 per cent, corresponding to their 10-year return period exceedance probability, using a binomial distribution and then the specification of Column 8 of Table 1 re-estimated. This was done 1,000 times, where for each simulation we recuperated the $t$-statistics on our ND shocks variables and their lags. We provide the corresponding the $p$-values of our actual estimates relative to the distribution obtained from the simulations in Table 3.6. As can be seen, the test confirms the significance (at 10% by the least) at time t-2 of human loss shock ($p$-value=0.002) and economic loss shock ($p$-value=0.062). The impact of natural disaster shocks in our study is quite extreme between other random events with similar degree of rarity.

**[Table 3.6 about here].**

### 3.4.3 Alternative Definition of 'Salient' ND Events

We define salient NDs very clearly as those that had a return period of at least 10 years. However, admittedly, there is no a priori reason to settle on a 10-year 'return period', i.e., a 10% probability event, as a the minimum threshold for which to identify ND shocks that matter for environmental voting. To explore how sensitive our results are to this choice we investigate different values of return level to define ND shocks and re-estimate the baseline regressions with 4 lag lengths (similar to Column 10 of Table 3.2). Figures 3.4 and 3.5 show the estimated the contemporaneous and lagged coefficients on economic and human losses, along with their 95% confidence bands, using various return period thresholds ranging from 2 to 20 years. Accordingly, while the coefficients at $t$, $t-1$, $t-3$, and $t-4$ are consistently insignificant for both economic and human losses, no matter what return period threshold we choose, this is not the case for the coefficients of the $t-2$ lags. Rather significant (at the 95% level) effects are found at return period thresholds between 6 years (16.7%) and 12 years (8.3%) for human loss shocks and between 3 years (33.3%) and 13 years (7.7%) for economic loss shocks, although in some cases only at the 10 per cent level for the latter.[21] Moreover, for the human loss estimate the coefficient appears highest for the 10-year return period definition, while it remains relatively stable for the significant range for economic losses. We can thus be fairly confident that our main results hold as long as we define the salience of the ND shocks within the neighborhood of a 10-year return period.

**[Figure 3.4, and 3.5 about here].**

### 3.4.4 Heterogeneity Treatment Effects

Our results thus far represent average treatment effects of ND shocks on senatorial environmental voting. Feasibly the effects could differ within our sample. We explore treatment heterogeneity along several fronts below, the results of which are all illustrated in Table 3.7.

**[Table 3.7 about here].**

Our baseline regressions implicitly assume that legislators' responses to ND shocks are stable over time. However, it is well known that American politics, at both mass and elite level, has become more polarised over time (Garand, 2010). To investigate how this might have affected our ND and environmental voting relationship we create two dummies breaking down our sample period into that pre- and that post-1990, and interact these with the ND shocks and their lags for our base specification. The results are illustrated in Column (1) of Table 3.7. For both periods, significant responses of senators to ND shocks are found at 2 years after the

[21] The percentages in parentheses indicate the rarities of the events corresponding to the return periods

shocks, but such responses are statistically and quantitatively weaker after 1990. For example, senators' environmental friendliness is 3.54 points 2 years after a human loss shock (significant at 1%) but dropped by 3.01 points 2 years after an economic loss shock (significant at 10%). After 1990 senators are only significantly affected by human loss shocks, where a salient event year increase environmental voting by 1.86 points.

One caveat with using total annual losses to define salient events is it treats many multiple small events and one major event in the same manner. To indirectly address this issue, in Column (2), we interact each shock with binary variables that indicate whether there was statewide Presidential Disaster Declaration (SPDD) in the year when the shock occurred.[22] PDD, which are requested by governors of the affected areas and decided by the president, are required for the allocation of disaster relief from FEMA. Previous research suggests that though the granting of PDD status could be politically manipulated (Garrett and Sobel, 2003), it is a matter of public supervision where disasters strike and implies potential political consequences on the politicians, who act inappropriately (Gasper and Reeves, 2011). Our results suggest that SPDD urges Senators to react to ND shocks earlier and more strongly. More precisely, without a SPDD it takes senators 2 years to see a significant reaction, where, on average, the LCV scores increase by 2.72 points after a human loss shock and reduces by 1.33 points after an economic loss shock. In contrast, senators change their voting behaviour within a year in response to ND shocks when SPDD is declared. Moreover, this impact is larger than any of the average treatment effects at $t-2$: 10.93 for human loss shocks and -9.39 for economic loss shocks, both significant at 1%. The impact of an economic loss shock lasts for two years but declines to 6.97 points.

[22]PDDs could be for the whole state or some counties within the state only. As we examine the voting patterns of senators, we only pay attention to statewide events.

Column (3) compares the impact in election to non-election years, i.e., whether senators vote differently when they are up for election years.[23] However, as can be seen, regardless of whether senators were in an election year or not, they responded to human loss shocks 2 years after their occurrences as demonstrated through stronger support for environmental legislation. The reaction is nevertheless much stronger in election year where the coefficient roughly doubles.

We also examine whether characteristics of constituencies can affect the extent to which senators respond to ND shocks. In Columns (4) and (5) of Table 3.7, we depict the coefficients of the interaction terms of ND shocks with indicator variables for low risk and high income states respectively.[24] The results suggest that reactions of senators from these states to human loss shocks can be detected earlier and stronger. Just one year after the salient year of natural disasters, the LCV score of a senator from a low risk state and a high income state increases by 5.98 (significant at the 1% level) and 4.22 (significant at the 10% level) points respectively. One possible reason may be that inhabitants in states less exposed to natural disasters are less likely to expect and prepare for such an event. Hence, when natural disasters happen, they may leave large psychological shocks on voters as well as politicians, leading to a speedy and strong action from the legislators.

Categorising states by whether they are high or low income states, i.e., whether their personal income per capita is in the top quintile or not, also produces some interesting heterogeneity. More specifically, a significant impact from human losses is seen after a year for senators from high income states, but only after two years for low income states. This may be because in high income states there could be more people and groups that care about environmental issues

[23]We classify years as election years based on the class of senators and thus are assuming that all senators planned to re-run for their seat even in this was not the case.

[24]We define low-risk states as those less exposed to natural disasters in that their 10-year return level estimates for annual losses was within the lowest quintiles of the nationwide distribution; see in Figure 3.1 and 3.2.

in such communities. As a result, a human loss shock will more easily attract attention and drive elected senators to vote for more environmentally friendly.

Finally, we examine whether senators' personal characteristics affect their voting reaction to ND shocks in the last last three columns of Table 3.7. The estimates in Column (6) suggest that senators' response to ND shocks in the past is significant only if they actually occupied the post when the shocks occurred, and not if they were not elected yet. In contrast, the heterogeneous impact across affiliations in Column (7) is harder to interpret. If we use a more conservative level (5%) to determine statistical significance, then one can conclude that only Democratic senators are significantly affected by ND shocks. Taking the estimate at face value their scores two years following human loss shocks increases by 2.86%. Using a less conservative significance level, one would conclude that Democratic senators vote greener after both human loss shocks (2 year lags) and economic loss shocks (contemporaneously). In contrast, non-Democratic senators only respond to human loss shock (at 0 and 2 year lags) assuming that 10 per cent is the appropriate cut-off for significance. Finally, Column (8) suggests that only male Senators actually respond to human loss shocks.

## 3.5 Counter-factual analysis

In this section we ask how the Senate might have performed if there had been no ND shocks. To this end we use the baseline regression results (Column 8 of Table 3.2) to predict yearly LCV scores for each senator but setting all the economic and human ND loss variables to zero and adding up the observed residuals. Then the deviation of the average real score from the average simulated score can be attributable to the impact of ND shocks ceteris paribus. We do this separately for human loss shocks and economic loss shocks as well as a combination of the two. One may want to note that in our predictions we assume that all controls are significant predictors but only use the significant coefficients for the ND variables.

Figure 3.6 visualises our counterfactual analysis, where we compare the average LCV scores of senators (solid lines) to their ND free conterfactuals (dashed lines). The bar graphs represent the gap between the real scores and the simulated scores, or in other words, the impacts of ND shocks, where grey bars indicate positive and black bars negative impacts. Accordingly, during our sample period human loss shocks add to LCV score of the average senator up to 0.95 (1976) points, where the average effect is 0.48 points per year. In contrast, economic loss shocks reduce the average LCV score by up to 0.47 (2013) points and by 0.18 points on average. Overall, the combination of both types of shocks has a net positive impact and thus natural disaster losses have on average benefited environmentally friendly bills by about 0.30 points.

**[Figure 3.6 about here].**

## 3.6 Conclusions

Ideally elected politicians will act with their voters' best interests at heart. The occurrences of natural disasters offers researchers a quasi-natural experiment to investigate to what extent this is the case. More precisely, the often devastating human and monetary losses due to natural disasters set the context for possibly bringing about sudden changes in politicians' support of environmental issues. While, on the one hand, they may be inclined to prioritise the immediate economic needs after a disastrous event, casting environmental concerns aside, they may also consider supporting environment issues more urgently in order to reduce the impacts of natural hazards in the future.

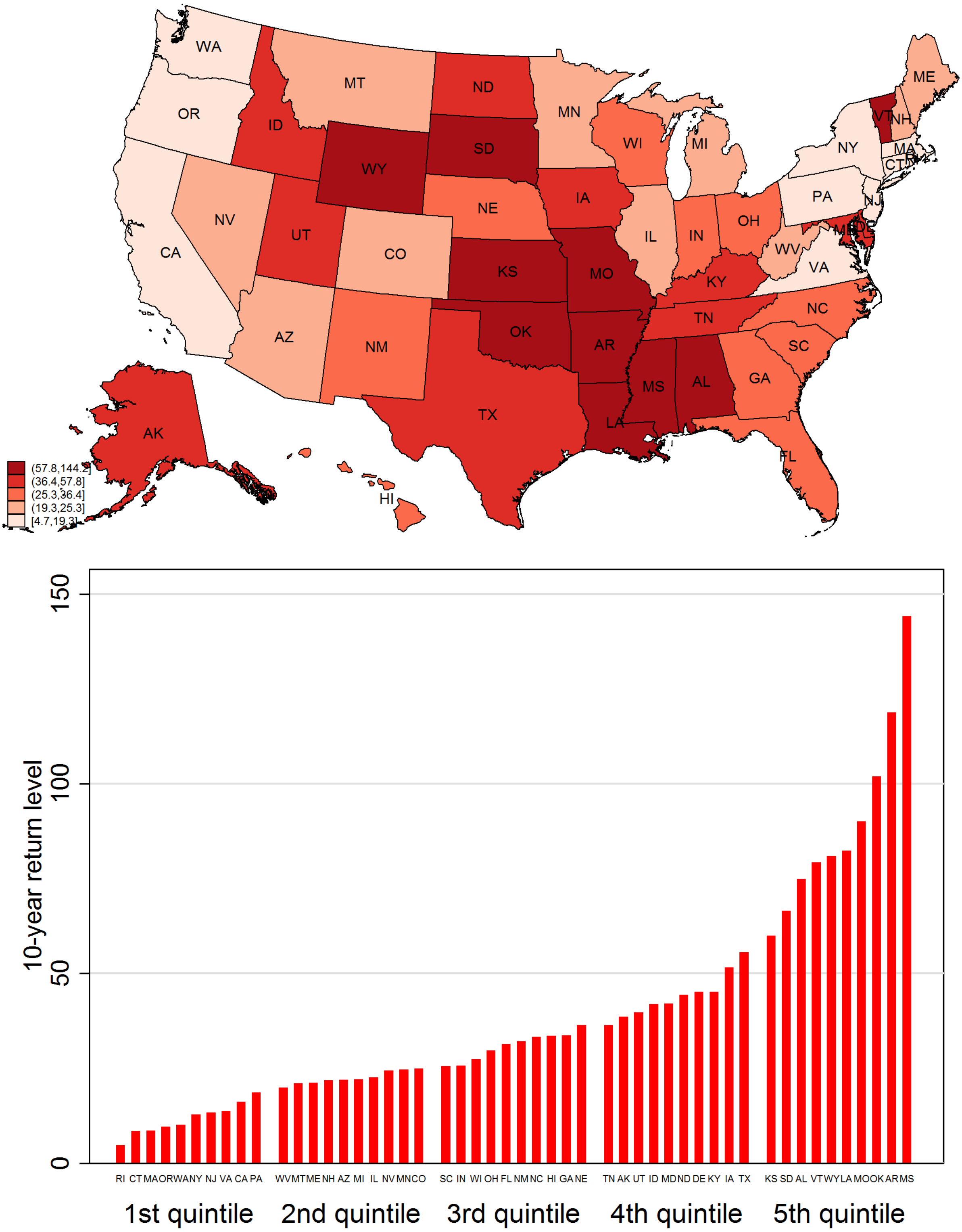
Our study, using a long panel of senatorial environmental voting behaviour and state level salient natural disaster losses, shows that senators are indeed responsive to the losses of their electorates after important natural disasters. However, their reaction in terms of voting for environmental friendly legislation is not immediate and is short-lived. The observed gap of two years between the occurrences of the natural shocks and changes in the environmental friendliness of senators perhaps suggest that such changes are not driven by immediate self-reflection and self-motivation of senators themselves, but rather through gradual interactions with external pressures, such as media coverage, public opinion, and advocacy groups. Our additional findings that senators from low risk, high income states and those profiting from statewide Presidential Disaster Declaration respond one year earlier than others further supports this possibility. In addition, the fact that any impact appears to be short-lived may reflect bounded rationality: impacts of natural disasters on senators disappear rapidly as other concerns arise.

In considering how senators react to natural disasters we find strong evidence that senators vote more favourably on environmentally friendly legislation if there is an extreme number of injuries and fatalities in their constituencies after natural disasters, and weaker evidence that they vote against the environment if there are exceptional monetary losses. These counteracting forces may help explain why the attitude of politicians toward environmental issues, on many occasions, seems unaltered despite the occurrences of major events, as these tend to come with extreme losses both in human and economic terms.

Finally, it should be acknowledged that one weakness of our study is that in identifying the important natural disaster event years used to identify any causal effects between natural disasters and senatorial voting behaviour we are assuming that the distribution of possible losses has remained stable over our 44 year sample period and that there is no temporal clustering of events. This may be an arguably unrealistic assumption and one could possibly explore this by modelling such changes explicitly, although our sample period may be too short to detect such effects. In addition, it is also interesting to test whether similar voting patterns can be observed at the House of Representatives. A difficulty that may arise in doing so, however, is that the boundaries of congressional districts have not been consistent over time due to the redistricting.

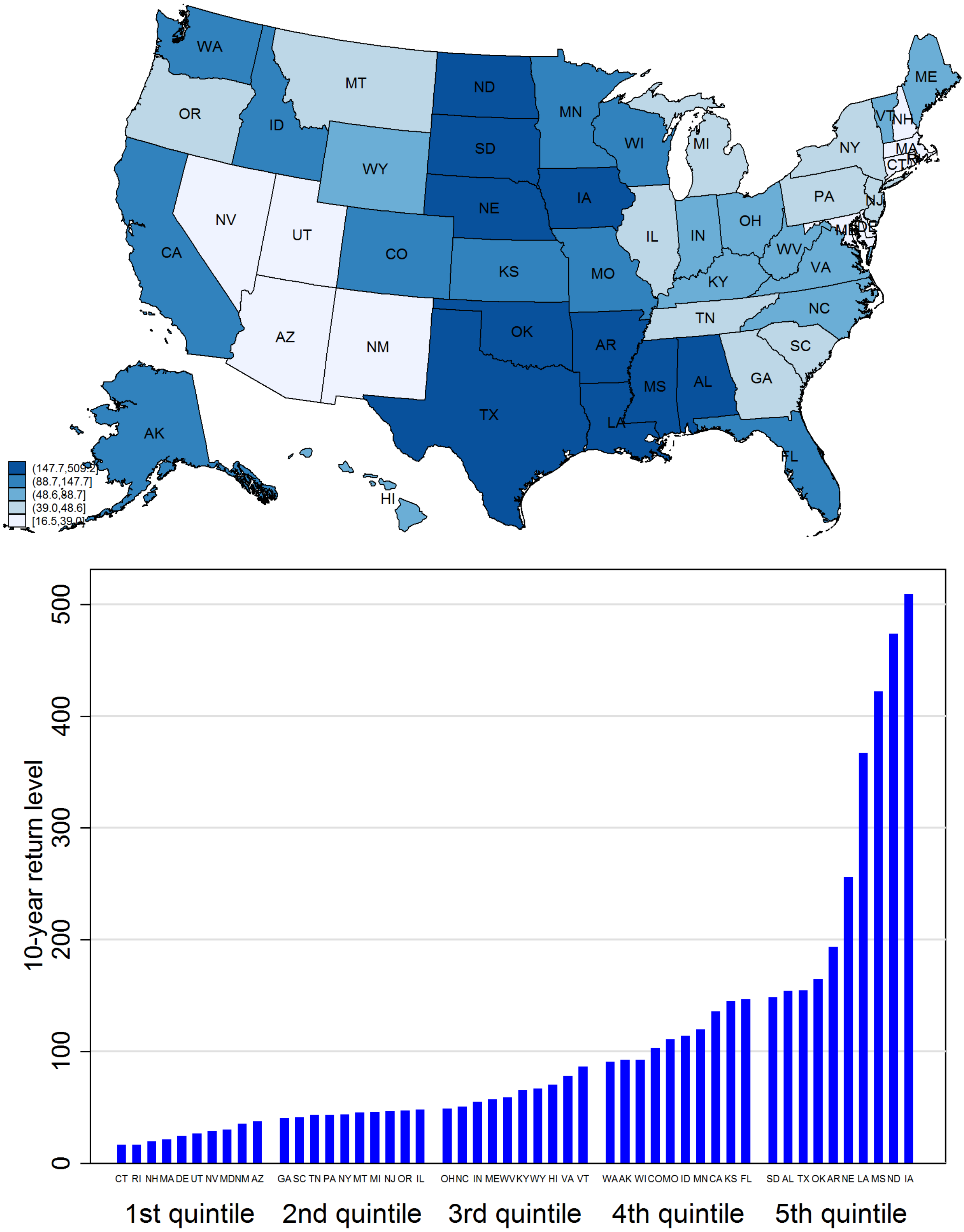
**Figure**

**Figure 3.1: Estimates of 10-year return level for annual human damages caused by natural disasters by state**



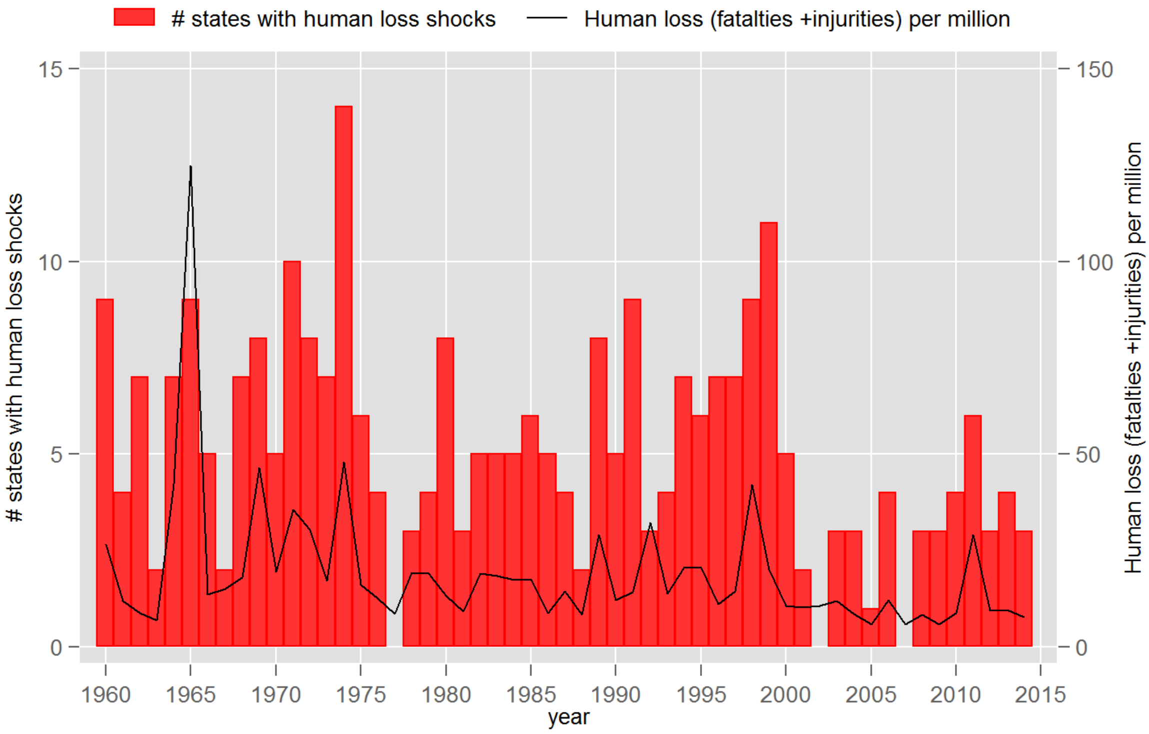

Source: Authors calculated from SHELDUS data between 1960-2014 for 50 states that have Senators. The damages are calculated as the total number of people injured or killed per 1 million heads by natural disasters of all kinds. See text for details.

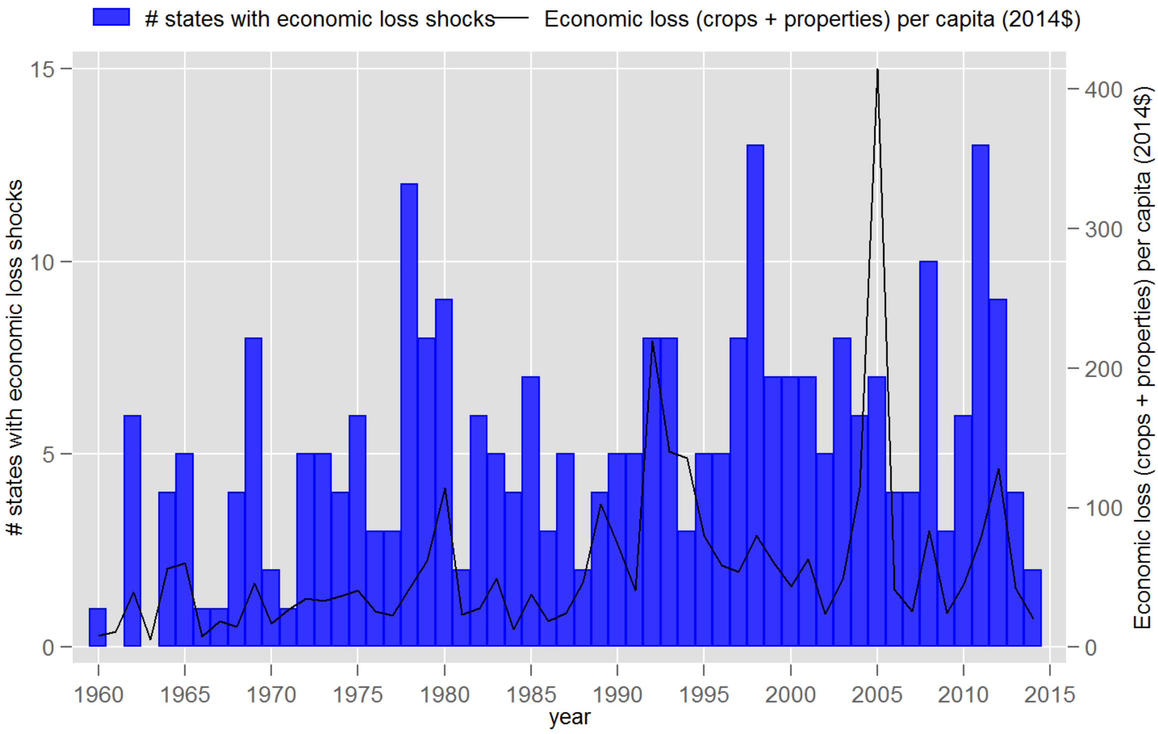
**Figure 3.2: Estimates of 10-year return level for annual economic damages caused by natural disasters by state**




Source: Authors calculated from SHELDUS data between 1960-2014 for 50 states that have Senators. The damages are calculated as the total damages to crops and properties (in 2014 USD) per capita by natural disasters of all kinds. See text for details.

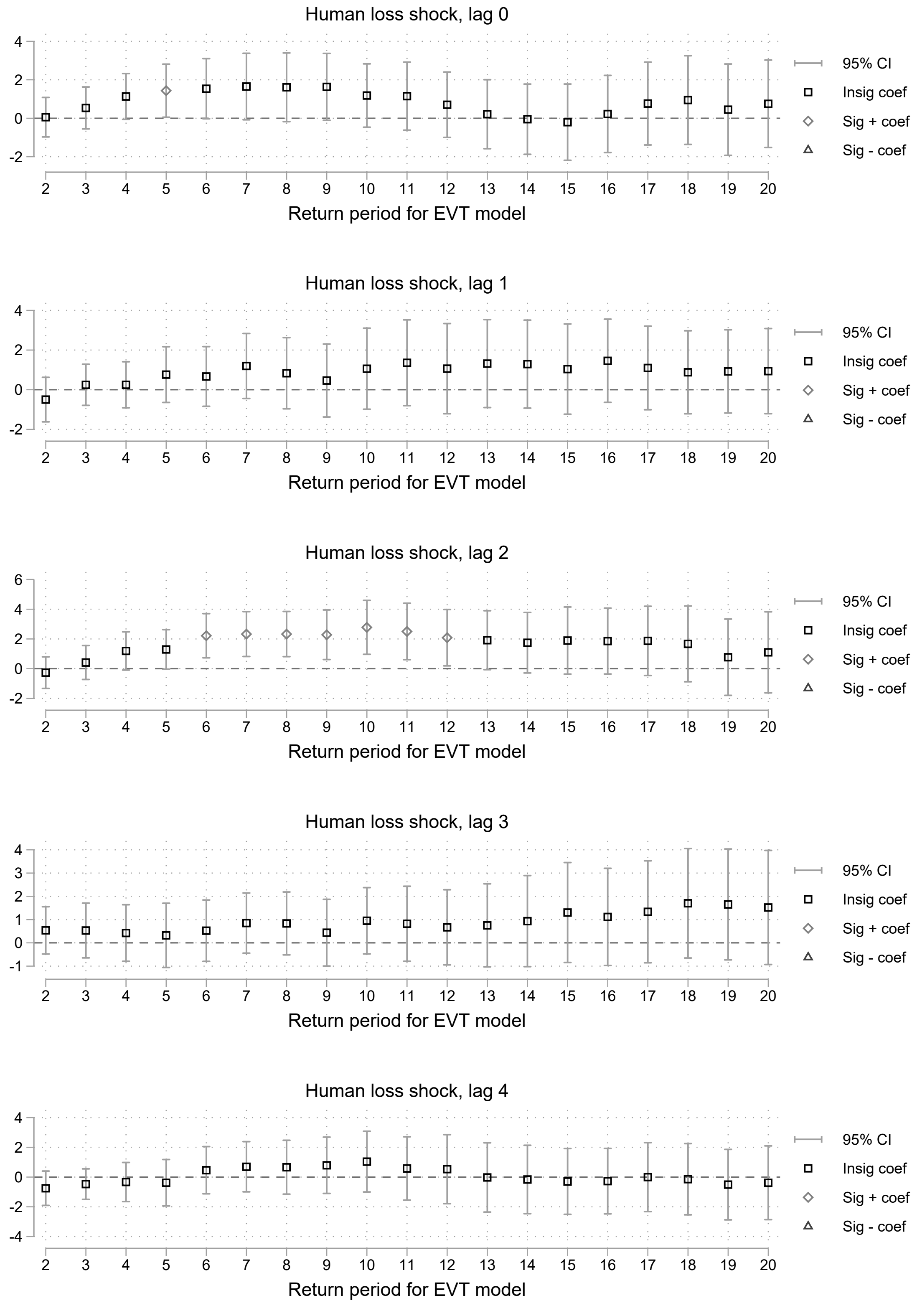
**Figure 3.3: Natural disaster shocks over time**



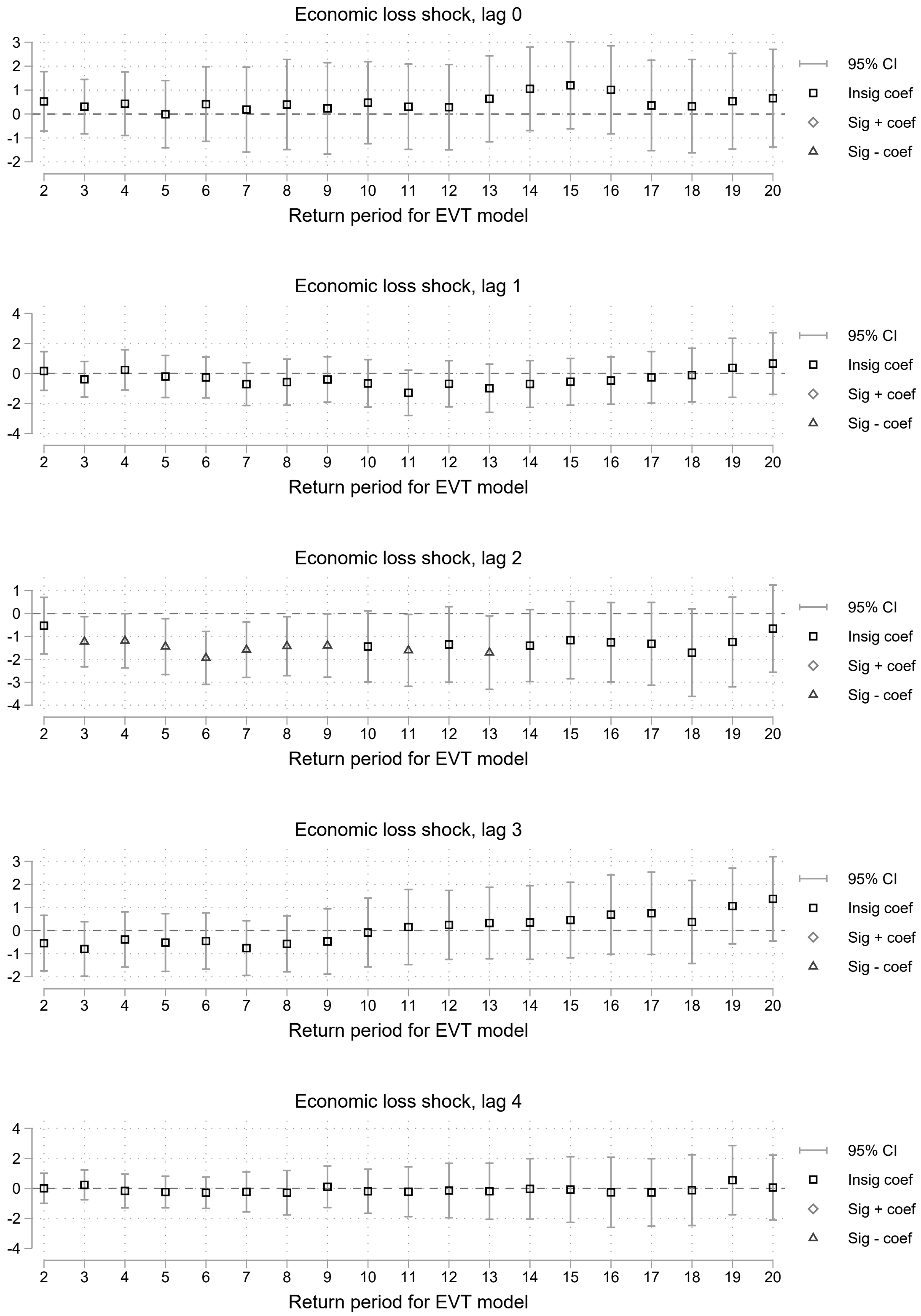

*Source:* Authors computed from the SHELDUS data for 50 states that have Senators. Human losses are the sum of fatalities and injuries. Economic losses are the sum of damages (in 2014 dollars) to crops and properties caused by natural disasters. Economic/human loss shocks are the years that economic/human losses of a particular state exceed their 10-year return levels as detailed in Figure 3.1 and 3.2.

**Figure 3.4: Return period sensitivity for human loss shocks**



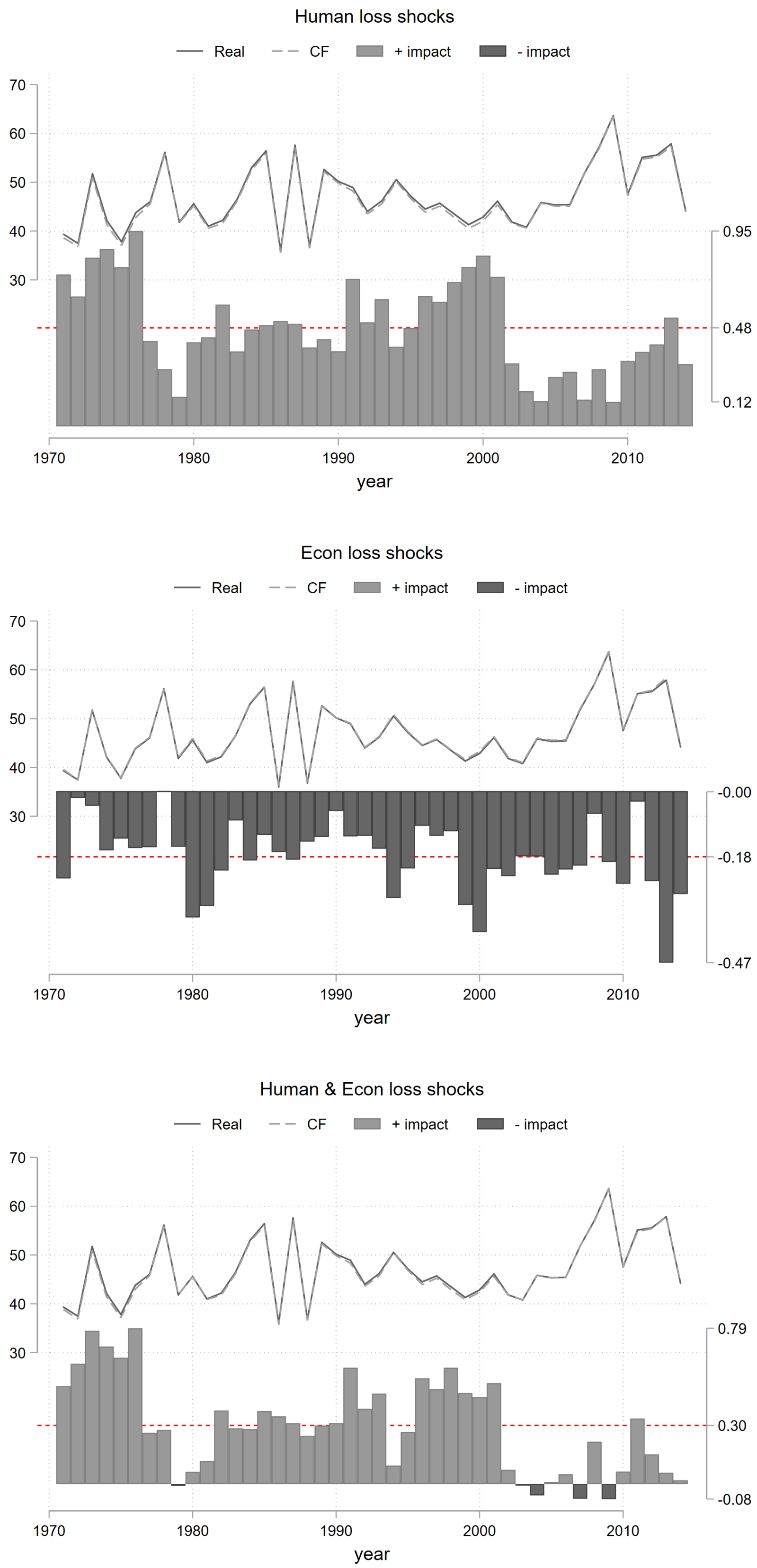

The figure illustrates the coefficients and confidence intervals of human loss shocks and their lags in the baseline regression using FE with 4 lags of the shocks (Column 10 of Table 1), where the shocks are defined by varying values of return periods in the EVT model. Significant coefficients are determined at the 5% level.

## Figure 3.5: Return period sensitivity for economic loss shocks




The figure illustrates the coefficients and confidence intervals of economic loss shocks and their lags in the baseline regression using FE with 4 lags of the shocks (Column 10 of Table 1), where the shocks are defined by varying values of return periods in the EVT model. Significant coefficients are determined at the 5% level.

## Figure 3.6: Counterfactual analysis: Baseline regression




The figure compares the real average LCV score of the Senate over time (solid lines) with the conterfactual scores supposed there were no human loss shocks (top panel), no economic loss shocks (middle panel) and no ND shocks (bottom panel). The bars indicates the gap between two lines. The lines use the left axes, the bars use the right axes.

# Tables

**Table 3.1: Summary statistics**

| VARIABLES | (1)<br>N | (2)<br>mean | (3)<br>sd | (4)<br>min | (5)<br>max |
|---|---|---|---|---|---|
| Annual legislators' LCV score (0-100 scale) | 4,414 | 46.99 | 34.50 | 0 | 100 |
| Human loss shocks (10-year return) | 4,414 | 0.0995 | 0.299 | 0 | 1 |
| Economic loss shocks (10-year return) | 4,414 | 0.116 | 0.321 | 0 | 1 |
| NOMINATE dim. 1 (ideology) | 4,414 | 0.00264 | 0.354 | -0.762 | 0.919 |
| NOMINATE dim. 2 (ideology) | 4,414 | -0.0663 | 0.449 | -1 | 1 |
| Democrat [binary] | 4,414 | 0.519 | 0.500 | 0 | 1 |
| First year at the Senate [binary] | 4,414 | 0.0662 | 0.249 | 0 | 1 |
| Senator in election year [binary] | 4,414 | 0.167 | 0.373 | 0 | 1 |
| Age | 4,414 | 58.55 | 10.37 | 31 | 100 |
| Male senator [binary] | 4,414 | 0.927 | 0.260 | 0 | 1 |
| Share of black voters | 4,414 | 0.0998 | 0.0936 | 0.00186 | 0.380 |
| Share of 18-29 voters | 4,414 | 0.257 | 0.0438 | 0.178 | 0.420 |
| Share of 30-44 voters | 4,414 | 0.285 | 0.0360 | 0.213 | 0.443 |
| Share of 45-64 voters | 4,414 | 0.293 | 0.0386 | 0.203 | 0.395 |
| Personal income, $2014 thousand | 4,414 | 32.48 | 9.404 | 13.92 | 66.92 |
| Real growth rate, % | 4,414 | 3.030 | 4.050 | -28.18 | 43.55 |
| Share of Air issues, % | 4,414 | 7.082 | 12.66 | 0 | 66.67 |
| Share of Clean Energy issues, % | 4,414 | 10.89 | 12.37 | 0 | 50 |
| Share of Dirty Energy issues, % | 4,414 | 35.65 | 13.96 | 0 | 66.67 |
| Share of Water issues, % | 4,414 | 28.51 | 13.83 | 0 | 71.43 |
| Share of Land issues, % | 4,414 | 33.41 | 19.86 | 0 | 85.71 |
| Share of Transportation issues, % | 4,414 | 8.056 | 11.35 | 0 | 53.85 |
| Share of Climate change issues, % | 4,414 | 5.629 | 11.48 | 0 | 40 |
| Share of Other issues, % | 4,414 | 19.69 | 13.45 | 0 | 50 |
| Average temperature ($^0C$) | 4,414 | 11.11 | 5.020 | -5.403 | 24.56 |
| Precipitation (inches) | 4,414 | 37.89 | 14.90 | 6.240 | 94.31 |

*Note:* Dirty Energy issues is shortened for Dirty Energy/Toxics/Public Right to Know issues. Water issues is shortened for Water, Oceans and Drilling issues. Land issues is shortened for Lands/Forest/Wildlife issues.

**Table 3.2: Senatorial votes for environment related issues in response to natural disaster(s)**

| VARIABLES | (1) OLS | (2) OLS | (3) OLS | (4) OLS | (5) OLS | (6) FE | (7) FE | (8) FE | (9) FE | (10) FE |
|---|---|---|---|---|---|---|---|---|---|---|
| Human loss shock, lag 0 | 1.65* | 1.54* | 1.68* | 1.67* | 1.72* | 0.81 | 0.82 | 1.06 | 1.08 | 1.18 |
| | (0.90) | (0.89) | (0.92) | (0.92) | (0.94) | (0.77) | (0.77) | (0.80) | (0.81) | (0.82) |
| Human loss shock, lag 1 | | 1.84* | 1.65* | 1.70* | 1.68* | | 0.90 | 0.96 | 1.03 | 1.06 |
| | | (0.96) | (0.95) | (0.96) | (0.96) | | (1.01) | (1.00) | (1.02) | (1.02) |
| Human loss shock, lag 2 | | | 3.49*** | 3.41*** | 3.44*** | | | 2.66*** | 2.70*** | 2.78*** |
| | | | (1.06) | (1.03) | (1.04) | | | (0.90) | (0.90) | (0.90) |
| Human loss shock, lag 3 | | | | 1.34 | 1.27 | | | | 0.91 | 0.95 |
| | | | | (0.87) | (0.86) | | | | (0.70) | (0.71) |
| Human loss shock, lag 4 | | | | | 1.20 | | | | | 1.04 |
| | | | | | (1.13) | | | | | (1.02) |
| Economic loss shock, lag 0 | -0.21 | -0.21 | -0.25 | -0.29 | -0.28 | 0.63 | 0.59 | 0.49 | 0.47 | 0.47 |
| | (1.07) | (1.08) | (1.10) | (1.11) | (1.12) | (0.81) | (0.81) | (0.84) | (0.84) | (0.85) |
| Economic loss shock, lag 1 | | -1.53 | -1.55 | -1.57 | -1.60* | | -0.51 | -0.61 | -0.62 | -0.66 |
| | | (0.93) | (0.93) | (0.94) | (0.94) | | (0.77) | (0.78) | (0.79) | (0.79) |
| Economic loss shock, lag 2 | | | -2.50** | -2.51** | -2.52** | | | -1.40* | -1.42* | -1.44* |
| | | | (0.99) | (1.00) | (1.00) | | | (0.75) | (0.77) | (0.77) |
| Economic loss shock, lag 3 | | | | -1.05 | -1.06 | | | | -0.046 | -0.084 |
| | | | | (0.95) | (0.96) | | | | (0.74) | (0.74) |
| Economic loss shock, lag 4 | | | | | -0.79 | | | | | -0.19 |
| | | | | | (0.94) | | | | | (0.73) |
| NOMINATE dim. 1 (ideology) | -58.5*** | -58.8*** | -59.2*** | -59.3*** | -59.3*** | -54.3*** | -54.4*** | -55.8*** | -56.7*** | -57.7*** |
| | (7.37) | (7.40) | (7.40) | (7.39) | (7.36) | (9.98) | (10.0) | (10.2) | (10.1) | (9.81) |
| NOMINATE dim. 2 (ideology) | -21.6*** | -21.5*** | -21.5*** | -21.4*** | -21.4*** | 6.92 | 7.22 | 7.85 | 8.53 | 9.89 |
| | (2.54) | (2.55) | (2.55) | (2.55) | (2.55) | (22.1) | (22.1) | (22.2) | (22.1) | (21.6) |
| Democrat [binary] | 14.0*** | 13.8*** | 13.6*** | 13.5*** | 13.5*** | -1.26 | -1.45 | -2.26 | -2.80 | -3.62 |
| | (4.72) | (4.75) | (4.75) | (4.74) | (4.73) | (9.92) | (9.90) | (9.95) | (9.90) | (9.60) |
| First year at the Senate [binary] | -0.94 | -0.92 | -1.06 | -1.02 | -1.01 | -1.65 | -1.64 | -1.73 | -1.71 | -1.70 |
| | (1.08) | (1.08) | (1.09) | (1.08) | (1.08) | (1.02) | (1.02) | (1.03) | (1.03) | (1.03) |
| Senator in election year [binary] | -0.38 | -0.38 | -0.40 | -0.40 | -0.39 | 0.0056 | 0.0083 | -0.010 | -0.016 | -0.015 |
| | (0.66) | (0.66) | (0.65) | (0.65) | (0.65) | (0.67) | (0.67) | (0.67) | (0.67) | (0.67) |
| Age | -0.10 | -0.10 | -0.10 | -0.10 | -0.10 | -0.19 | -0.19 | -0.20 | -0.20 | -0.21 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (0.065) | (0.065) | (0.064) | (0.064) | (0.064) | (0.35) | (0.36) | (0.36) | (0.37) | (0.37) |
| Male senator [binary] | -2.85 | -2.83 | -2.81 | -2.83 | -2.84 | | | | | |
| | (2.37) | (2.37) | (2.34) | (2.33) | (2.34) | | | | | |
| Share of black voters | 6.04 | 6.01 | 6.02 | 5.99 | 5.93 | -63.1 | -64.2 | -66.2 | -67.0 | -68.5 |
| | (11.8) | (11.8) | (11.7) | (11.6) | (11.6) | (93.2) | (93.7) | (95.1) | (95.4) | (95.9) |
| Share of 18-29 voters | -151** | -152** | -153** | -153** | -154** | -192 | -193 | -198 | -200 | -204 |
| | (58.9) | (59.0) | (59.0) | (59.0) | (59.0) | (129) | (129) | (127) | (127) | (127) |
| Share of 30-44 voters | -103* | -103* | -102* | -101* | -101* | -317** | -316** | -319** | -319** | -321** |
| | (59.1) | (58.7) | (57.8) | (57.5) | (57.3) | (139) | (139) | (137) | (136) | (135) |
| Share of 45-64 voters | -110 | -110 | -109 | -109 | -109 | -427*** | -426*** | -429*** | -431*** | -433*** |
| | (83.2) | (83.6) | (83.9) | (84.1) | (84.3) | (159) | (159) | (157) | (156) | (155) |
| Personal income, $2014 | 0.47*** | 0.47*** | 0.47*** | 0.47*** | 0.46*** | 0.47** | 0.46* | 0.44* | 0.43* | 0.42* |
| | (0.16) | (0.16) | (0.16) | (0.16) | (0.16) | (0.23) | (0.23) | (0.23) | (0.23) | (0.23) |
| Real growth rate, % | 0.065 | 0.066 | 0.063 | 0.064 | 0.067 | -0.081 | -0.080 | -0.081 | -0.081 | -0.077 |
| | (0.11) | (0.11) | (0.11) | (0.11) | (0.11) | (0.089) | (0.089) | (0.088) | (0.087) | (0.086) |
| Share of Air issues | -0.46*** | -0.48*** | -0.49*** | -0.48*** | -0.49*** | -0.19* | -0.19* | -0.19* | -0.19* | -0.19* |
| | (0.17) | (0.17) | (0.17) | (0.17) | (0.17) | (0.098) | (0.098) | (0.099) | (0.100) | (0.10) |
| Share of Clean Energy issues | -0.27** | -0.27** | -0.27** | -0.27** | -0.26** | 0.0063 | 0.0069 | 0.015 | 0.014 | 0.013 |
| | (0.12) | (0.11) | (0.11) | (0.11) | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) |
| Share of Dirty Energy issues | 0.67*** | 0.70*** | 0.69*** | 0.69*** | 0.70*** | -0.14*** | -0.14*** | -0.14*** | -0.14*** | -0.14*** |
| | (0.18) | (0.18) | (0.18) | (0.18) | (0.18) | (0.047) | (0.047) | (0.047) | (0.047) | (0.048) |
| Share of Water issues | 0.22** | 0.23** | 0.23** | 0.23** | 0.23** | 0.013 | 0.016 | 0.033 | 0.034 | 0.037 |
| | (0.088) | (0.088) | (0.087) | (0.087) | (0.087) | (0.062) | (0.062) | (0.064) | (0.064) | (0.065) |
| Share of Land issues | 0.46*** | 0.47*** | 0.47*** | 0.47*** | 0.47*** | -0.011 | -0.011 | -0.012 | -0.014 | -0.015 |
| | (0.099) | (0.099) | (0.099) | (0.098) | (0.097) | (0.050) | (0.050) | (0.050) | (0.050) | (0.050) |
| Share of Transportation issues | -0.045 | -0.063 | -0.054 | -0.049 | -0.049 | 0.018 | 0.018 | 0.020 | 0.020 | 0.020 |
| | (0.27) | (0.28) | (0.27) | (0.27) | (0.27) | (0.17) | (0.17) | (0.17) | (0.18) | (0.18) |
| Share of Climate change issues | 0.58*** | 0.59*** | 0.61*** | 0.62*** | 0.62*** | 0.38*** | 0.38*** | 0.41*** | 0.42*** | 0.42*** |
| | (0.15) | (0.15) | (0.14) | (0.14) | (0.14) | (0.091) | (0.091) | (0.093) | (0.094) | (0.094) |
| Share of Other issues | 0.58*** | 0.59*** | 0.58*** | 0.58*** | 0.58*** | 0.31*** | 0.31*** | 0.35*** | 0.35*** | 0.36*** |
| | (0.16) | (0.16) | (0.16) | (0.16) | (0.16) | (0.11) | (0.11) | (0.11) | (0.11) | (0.11) |
| Average temperature ($^0C$) | -0.26 | -0.26 | -0.25 | -0.25 | -0.25 | -1.11** | -1.13** | -1.12** | -1.10** | -1.12** |
| | (0.22) | (0.22) | (0.22) | (0.22) | (0.21) | (0.48) | (0.49) | (0.49) | (0.49) | (0.49) |
| Precipitation (inches) | 0.0061 | 0.0057 | 0.0030 | 0.0029 | 0.0031 | -0.064 | -0.064 | -0.070 | -0.070 | -0.070 |
| | (0.080) | (0.080) | (0.079) | (0.079) | (0.079) | (0.053) | (0.053) | (0.052) | (0.052) | (0.052) |
| Constant | 84.7 | 83.8 | 83.8 | 83.5 | 83.3 | 329*** | 329*** | 332*** | 334*** | 337*** |
| | (50.8) | (50.6) | (50.7) | (50.7) | (50.7) | (119) | (119) | (118) | (117) | (117) |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 4,414 | 4,414 | 4,414 | 4,414 | 4,414 | 4,414 | 4,414 | 4,414 | 4,414 | 4,414 |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| AIC | 38144.6 | 38140.8 | 38122.0 | 38117.0 | 38118.9 | 35884.7 | 35883.0 | 35868.9 | 35867.4 | 35865.6 |
| BIC | 38470.7 | 38473.2 | 38454.4 | 38443 | 38457.7 | 36197.9 | 36196.2 | 36182.2 | 36180.7 | 36178.8 |
| Number of id | | | | | | 381 | 381 | 381 | 381 | 381 |

Note: The dependent variable is annual LCV score of senators. Standard errors clustered at state level are in parentheses. *,**,*** are estimates significant at 10%, 5% and 1% respectively. Dirty Energy issues is shortened for Dirty Energy/Toxics/Public Right to Know issues. Water issues is shortened for Water, Oceans and Drilling issues. Land issues is shortened for Lands/Forest/Wildlife issues.

**Table 3.3: Robustness checks: Alternative specifications**

| VARIABLES | (1) FE | (2) FE | (3) FE | (4) FE | (5) FE | (6) FE | (7) FE | (8) FE | (9) FE | (10) FE | (11) GMM | (12) GMM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Human loss shock, lag 0 | 1.06 | 0.96 | | | 1.21 | 1.08 | | | 1.01 | 1.02 | 1.00 | 1.06 |
| | (0.80) | (0.88) | | | (0.78) | (0.85) | | | (0.93) | (0.86) | (0.93) | (0.93) |
| Human loss shock, lag 1 | 0.96 | 0.99 | | | 0.89 | 0.84 | | | 0.87 | 0.90 | 0.43 | 0.38 |
| | (1.00) | (1.05) | | | (1.01) | (1.07) | | | (1.02) | (1.02) | (0.91) | (0.92) |
| Human loss shock, lag 2 | 2.66*** | 2.94*** | 2.54*** | 2.82*** | 2.44** | 2.74*** | | | 2.76*** | 2.79*** | 2.81*** | 2.72*** |
| | (0.90) | (0.93) | (0.88) | (0.90) | (0.92) | (0.98) | | | (0.93) | (0.90) | (0.96) | (0.96) |
| Economic loss shock, lag 0 | 0.49 | 0.36 | | | | | 0.74 | 0.58 | 0.17 | 0.23 | 0.11 | 0.078 |
| | (0.84) | (0.95) | | | | | (0.81) | (0.90) | (0.92) | (0.93) | (0.93) | (0.94) |
| Economic loss shock, lag 1 | -0.61 | -0.52 | | | | | -0.33 | -0.29 | -0.70 | -0.56 | -1.15 | -1.17 |
| | (0.78) | (0.84) | | | | | (0.82) | (0.88) | (0.83) | (0.82) | (0.74) | (0.76) |
| Economic loss shock, lag 2 | -1.40* | -1.39 | -1.38* | -1.37* | | | -0.83 | -0.86 | -1.38 | -1.30 | -1.84** | -1.79** |
| | (0.75) | (0.85) | (0.71) | (0.81) | | | (0.75) | (0.84) | (0.85) | (0.82) | (0.84) | (0.83) |
| LCV score, lag 1 | | | | | | | | | 0.15*** | 0.14*** | 0.071** | 0.067** |
| | | | | | | | | | (0.021) | (0.022) | (0.029) | (0.030) |
| LCV score, lag 2 | | | | | | | | | 0.040* | 0.038* | -0.0073 | -0.0062 |
| | | | | | | | | | (0.022) | (0.023) | (0.026) | (0.025) |
| Observations | 4,414 | 3,661 | 4,414 | 3,661 | 4,414 | 3,661 | 4,414 | 3,661 | 3,659 | 3,659 | 3,329 | 3,329 |
| Number of id | 381 | 328 | 381 | 328 | 381 | 328 | 381 | 328 | 327 | 327 | 326 | 326 |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Lagged controls | N | Y | N | Y | N | Y | N | Y | N | Y | N | Y |

Note: The dependent variable is annual LCV score of senators. This table also includes control variables identical as Table 3.2 and up to 2 lags of all controls (where Lagged controls=Y). Standard errors clustered at state level are in parentheses. *,**,*** are estimates significant at 10%, 5% and 1% respectively.

## Table 3.4: Robustness check: Control for ADA Score

| VARIABLES | (1) OLS | (2) OLS | (3) OLS | (4) OLS | (5) OLS | (6) FE | (7) FE | (8) FE | (9) FE | (10) FE |
|---|---|---|---|---|---|---|---|---|---|---|
| Human loss shock, lag 0 | 1.66** | 1.53** | 1.66** | 1.70** | 1.72** | 0.85 | 0.87 | 1.12 | 1.14 | 1.19 |
| | (0.73) | (0.74) | (0.77) | (0.77) | (0.78) | (0.73) | (0.73) | (0.77) | (0.79) | (0.79) |
| Human loss shock, lag 1 | | 1.75* | 1.54* | 1.62* | 1.61* | | 0.96 | 1.02 | 1.07 | 1.08 |
| | | (0.88) | (0.86) | (0.87) | (0.88) | | (0.94) | (0.93) | (0.94) | (0.94) |
| Human loss shock, lag 2 | | | 3.52*** | 3.46*** | 3.48*** | | | 2.86*** | 2.86*** | 2.90*** |
| | | | (0.95) | (0.92) | (0.92) | | | (0.85) | (0.85) | (0.85) |
| Human loss shock, lag 3 | | | | 0.50 | 0.45 | | | | 0.35 | 0.38 |
| | | | | (0.78) | (0.77) | | | | (0.66) | (0.66) |
| Human loss shock, lag 4 | | | | | 0.65 | | | | | 0.54 |
| | | | | | (1.08) | | | | | (0.96) |
| Economic loss shock, lag 0 | -1.16 | -1.15 | -1.19 | -1.23 | -1.24 | 0.44 | 0.40 | 0.31 | 0.27 | 0.29 |
| | (0.97) | (0.97) | (0.99) | (1.00) | (1.01) | (0.78) | (0.78) | (0.80) | (0.80) | (0.81) |
| Economic loss shock, lag 1 | | -2.25** | -2.24** | -2.27** | -2.29** | | -0.70 | -0.78 | -0.81 | -0.82 |
| | | (0.89) | (0.89) | (0.90) | (0.90) | | (0.75) | (0.75) | (0.76) | (0.75) |
| Economic loss shock, lag 2 | | | -2.31*** | -2.31*** | -2.31*** | | | -1.22* | -1.25* | -1.25* |
| | | | (0.76) | (0.77) | (0.77) | | | (0.62) | (0.64) | (0.64) |
| Economic loss shock, lag 3 | | | | -1.70** | -1.70** | | | | -0.41 | -0.43 |
| | | | | (0.81) | (0.81) | | | | (0.69) | (0.70) |
| Economic loss shock, lag 4 | | | | | -0.67 | | | | | 0.038 |
| | | | | | (0.92) | | | | | (0.72) |
| ADA score | 0.78*** | 0.78*** | 0.78*** | 0.78*** | 0.78*** | 0.49*** | 0.49*** | 0.50*** | 0.50*** | 0.50*** |
| | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.034) | (0.034) | (0.034) | (0.034) | (0.034) |
| Observations | 4,368 | 4,368 | 4,368 | 4,368 | 4,368 | 4,368 | 4,368 | 4,368 | 4,368 | 4,368 |
| AIC | 36884.9 | 36874.5 | 36850.6 | 36848.0 | 36846.9 | 34870.3 | 34867.8 | 34850.3 | 34849.7 | 34849.1 |
| BIC | 37210.3 | 37200 | 37169.7 | 37173.5 | 37172.4 | 35183 | 35180.5 | 35163 | 35162.4 | 35161.8 |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Number of id | | | | | | 370 | 370 | 370 | 370 | 370 |

Note: The dependent variable is annual LCV score of senators. This table also includes control variables identical as Table 3.2 with ideology variables (NOMINATE estimates) replaced by Annual ADA score. Standard errors clustered at state level are in parentheses. *,**,*** are estimates significant at 10%, 5% and 1% respectively

## Table 3.5: Placebo test: The impact of future ND shocks

| | L=Lag | | | | | L=Lead | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| VARIABLES | FE | FE | FE | FE | FE | FE | FE | FE | FE | FE |
| Human loss shock, L0 | 0.81 | 1.01 | 1.23 | 1.33 | 1.27 | 0.81 | 1.00 | 0.87 | 1.00 | 0.84 |
| | (0.77) | (0.80) | (0.86) | (0.87) | (0.85) | (0.77) | (0.80) | (0.83) | (0.86) | (0.86) |
| Human loss shock, L1 | | 0.99 | 0.96 | 1.01 | 1.16 | | -0.077 | 0.23 | 0.059 | 0.057 |
| | | (1.00) | (0.99) | (1.03) | (1.05) | | (0.78) | (0.75) | (0.78) | (0.79) |
| Human loss shock, L2 | | | 2.96*** | 3.04*** | 3.17*** | | | -0.76 | -0.66 | -0.60 |
| | | | (0.89) | (0.91) | (0.92) | | | (0.92) | (0.97) | (0.99) |
| Human loss shock, L3 | | | | 0.99 | 1.12 | | | | -1.66 | -1.72* |
| | | | | (0.74) | (0.77) | | | | (1.00) | (1.01) |
| Human loss shock, L4 | | | | | 0.90 | | | | | -0.21 |
| | | | | | (1.01) | | | | | (0.86) |
| Economic loss shock, L0 | 0.63 | 0.52 | 0.50 | 0.53 | 0.62 | 0.63 | 0.57 | 0.75 | 0.78 | 0.88 |
| | (0.81) | (0.81) | (0.84) | (0.87) | (0.94) | (0.81) | (0.81) | (0.79) | (0.85) | (0.93) |
| Economic loss shock, L1 | | -0.63 | -0.59 | -0.65 | -0.58 | | -0.028 | -0.093 | -0.062 | 0.14 |
| | | (0.74) | (0.76) | (0.78) | (0.78) | | (0.80) | (0.80) | (0.84) | (0.88) |
| Economic loss shock, L2 | | | -1.84** | -1.73* | -1.80** | | | 1.14 | 1.08 | 1.12 |
| | | | (0.79) | (0.87) | (0.88) | | | (0.73) | (0.75) | (0.79) |
| Economic loss shock, L3 | | | | 0.16 | 0.26 | | | | -0.23 | -0.12 |
| | | | | (0.78) | (0.78) | | | | (0.76) | (0.78) |
| Economic loss shock, L4 | | | | | -0.054 | | | | | 0.31 |
| | | | | | (0.81) | | | | | (0.75) |
| Constant | 329*** | 345*** | 321** | 316** | 306** | 329*** | 344*** | 315** | 313** | 303** |
| | (119) | (119) | (121) | (124) | (124) | (119) | (120) | (122) | (127) | (127) |
| Observations | 4,414 | 4,314 | 4,211 | 4,112 | 4,011 | 4,414 | 4,314 | 4,211 | 4,112 | 4,011 |
| Number of id | 381 | 379 | 362 | 362 | 349 | 381 | 379 | 362 | 362 | 349 |
| AIC | 35884.7 | 35083.0 | 34270.0 | 33503.5 | 32724.2 | 35884.7 | 35087.0 | 34284.2 | 33516.2 | 32739.1 |
| BIC | 36197.9 | 35395.1 | 34587.2 | 33813.3 | 33032.7 | 36197.9 | 35405.5 | 34595.1 | 33826 | 33047.6 |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |

Note: The dependent variable is annual LCV score of senators. This table also includes control variables identical as Table 3.2. Standard errors clustered at state level are in parentheses. *,**,*** are estimates significant at 10%, 5% and 1% respectively.

## Table 3.6: Monte Carlo permutation test

| Lag | Human loss shock | Economic loss shock |
|---|---|---|
| 0 | 1.32 [.206] | 0.59 [.524] |
| 1 | 0.96 [.312] | -0.79 [.424] |
| 2 | 2.96 [.002] | -1.86 [.062] |

This table illustrates the t-statistics of natural disaster shocks and their lags in the benchmark regression and the 2-tail p-values (in brackets) of these statistics derived from a Monte Carlo permutation test. The distribution of t-statistics is constructed from the 1,000 repetitions of the benchmark regression with natural disaster shocks randomly reassigned to each state-year pair by a binomial distribution with a probability of 10%. The p-values are calculated as the percentage of t-statistics in the distribution that are more extreme than the benchmark values.

## Table 3.7: Heterogeneity analysis

| | Year characteristics | | | | | | State characteristics | | | | Senator characterisitcs | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | | (5) | | (6) | | (7) | | (8) | |
| | Before 1990 | Since 1990 | SPDD year | Other year | Election year | Other | Low risk | Other | High income | Other | Incumbent | Other | Democrat | Other | Male | Female |
| Human loss shock, lag 0 × | 1.11 | 1.27 | 2.96 | 1.06 | 0.85 | 1.09 | 0.78 | 1.03 | 1.97 | 0.76 | 1.10 | | -0.01 | 2.28* | 1.29 | -3.21 |
| | (1.22) | (0.97) | (5.74) | (0.82) | (1.65) | (0.88) | (1.31) | (0.92) | (1.97) | (0.93) | (0.80) | | (1.05) | (1.15) | (0.82) | (2.57) |
| Human loss shock, lag 1 × | 1.19 | 0.91 | 10.93** | 0.92 | -2.22 | 1.50 | 5.98*** | -0.08 | 4.22* | 0.15 | 1.20 | -3.60 | 1.07 | 0.96 | 1.05 | -1.28 |
| | (1.40) | (1.09) | (4.84) | (1.02) | (2.31) | (0.93) | (2.00) | (1.08) | (2.48) | (1.01) | (1.00) | (3.63) | (1.20) | (1.37) | (0.98) | (4.16) |
| Human loss shock, lag 2 × | 3.54** | 1.86* | -0.18 | 2.72*** | 4.21** | 2.34** | 0.57 | 3.05*** | 3.10 | 2.49** | 2.83*** | 0.89 | 2.86** | 2.49* | 2.68*** | 2.24 |
| | (1.53) | (0.96) | (2.33) | (0.89) | (1.74) | (0.99) | (2.11) | (0.98) | (1.90) | (1.03) | (0.95) | (2.85) | (1.20) | (1.27) | (0.90) | (3.60) |
| Economic loss shock, lag 0 × | -1.22 | 1.45 | -1.47 | 0.46 | -0.46 | 0.65 | -1.83 | 1.02 | 0.10 | 0.50 | 0.47 | | 2.37* | -1.58 | 0.48 | 0.66 |
| | (1.67) | (1.05) | (3.90) | (0.84) | (1.91) | (0.89) | (1.38) | (0.93) | (1.74) | (0.92) | (0.83) | | (1.29) | (1.06) | (0.84) | (3.23) |
| Economic loss shock, lag 1 × | -1.65 | -0.19 | -9.39*** | -0.54 | 0.68 | -0.82 | -1.27 | -0.56 | -0.37 | -0.73 | -0.68 | 0.96 | -0.20 | -1.15 | -0.73 | 0.82 |
| | (1.57) | (0.95) | (1.36) | (0.78) | (2.21) | (0.76) | (1.78) | (0.93) | (1.44) | (0.91) | (0.79) | (3.10) | (1.29) | (0.79) | (0.80) | (1.95) |
| Economic loss shock, lag 2 × | -3.01* | -0.48 | -6.97*** | -1.33* | -2.60 | -1.17 | -2.49* | -1.07 | -2.57 | -1.15 | -1.59* | 0.61 | -1.51 | -1.31 | -1.23 | -3.77 |
| | (1.58) | (0.99) | (1.74) | (0.77) | (1.94) | (0.84) | (1.46) | (0.90) | (1.82) | (0.85) | (0.85) | (2.83) | (1.20) | (1.02) | (0.79) | (3.28) |
| Observations | 4,414 | | 4,414 | | 4,414 | | 4,414 | | 4,414 | | 4,414 | | 4,414 | | 4,414 | |
| AIC | 35861.68 | | 35865.64 | | 35864.27 | | 35853.46 | | 35862.68 | | 35865.89 | | 35859.32 | | 35865.65 | |
| BIC | 36174.91 | | 36178.88 | | 36177.51 | | 36166.69 | | 36175.92 | | 36179.13 | | 36172.56 | | 36178.88 | |

Note: The dependent variable is annual LCV scores of senators. Besides interaction terms, regressions in this table also include control variables identical as Table 3.2 (including senator FE and year FE). Standard errors clustered at state level are in parentheses. *,**,*** are estimates significant at 10%, 5% and 1% respectively

## 3.A Appendix A: Extreme Value Theory (EVT) and Peaks Over a Threshold model (POT)

This appendix explains how we apply the Extreme Value Theory (EVT) and Peaks Over a Threshold model (POT) to construct the measures of natural disaster shocks. We examine the sequence of intensity of annual damages (in terms of either economic or human cost) $\{X_{j1}, X_{j2}, ...X_{jt}\}$ caused by ND in state $j$ (among 50 states), of which we have observations over 55 years (between 1960 and 2014) thanks to the SHELDUS database.[25] We are interested in modelling the unknown 'fat-tail' distribution of the maximum of the intensity sequence, which is assumed to be independent and identically distributed (i.i.d): $M_{jt} = \max\{X_{j1}, X_{j2}, ..., X_{jt}\}$. If we can normalise $\{M_{jt}\}$ by appropriate sequences of constants $\{a_{jt} > 0\}$ and $\{b_{jt}\}$ to obtain a non-degenerate distribution function $G_j$ for all $y \in \mathbb{R}$:

$$Pr\left\{\frac{M_{jt} - b_{jt}}{a_{jt}} \leq y\right\} \rightarrow G(y) \text{ as } t \rightarrow \infty \tag{3.A.1}$$

then by the Extremal Types Theorem (Fisher and Tippett, 1928), $G(y)$ must fall into one of 3 extreme value distribution families: Fréche, Gumbel or Weilbell. Furthermore, these families are specific cases of a single parametric distribution, namely the Generalised Extreme Value (GEV) (Jenkinson, 1955). This allows us to approximate the distribution of its maximum $\{M_{jt}\}$ by a GEV distribution, which is characterised by 3 parameters: location ($\mu_j$), scale ($\sigma_j$), and shape ($\xi_j$):[26]

[25] $t$ is the subscription for year.

[26] We use subscription $j$ for the GEV distribution function and its parameters here to hightlight the fact that we model state $j$ separately. As revealed by its name, the parameter $\xi_j$ control the shape of the GEV. It falls into Fréche, Gumbel or Weilbell families if $\xi > 0$, $\xi \rightarrow 0$ and $\xi < 0$ respectively.

$$Pr\{M_{jt} \leq z\} \approx G_j(z) = \exp\left\{-\left[1+\xi_j\left(\frac{z-\mu_j}{\sigma_j}\right)\right]^{-1/\xi_j}\right\}, \quad -\infty < z < \infty \tag{3.A.2}$$

Then the positive excesses over a threshold $u_j$ large enough ($y_{jk} = X_{jk} - u_j$ conditional on $X_{jk} > u_j$) approximate a generalised Pareto distribution (GPD) (Pickands, 1975):

$$Pr\{X_{jk} - u_j \leq y | X_{jk} > u_j\} \approx H_j(y) = 1 - \left(1 + \frac{\xi_j y}{\sigma_j + \xi_j(u_j - \mu_j)}\right)^{-1/\xi_j} \tag{3.A.3}$$

Intuitively, as we are modelling the upper tail of an i.i.d distribution, only observations on the right matter hence the approach requires the selection of a threshold $u_j$ to determine observations used for the approximation. The GPD $H_j(y)$ includes 2 parameters: a shape parameter $\xi_j$, which is the same as the shape parameter of GEV in (3.A.2) and a scale parameter $\tilde{\sigma}_j = \sigma_j + \xi_j(u_j - \mu_j)$, both of which can be estimated using Maximum Likelihood Estimator (MLE) and observed positive threshold excesses. The approach is sensitive to the choice of threshold $u_j$ as there is a tradeoff between unbiasedness and accuracy of the estimates. As only observations that exceed the threshold enter the estimation, a lower threshold retains more observations, yielding lower standard errors but at the cost of possible violation to the asymptotic basis of the model, which may cause biasness. In practice, a small threshold is preferable as long as the limit model can provide a reasonable approximation (Coles, 2001).

The selection of such a threshold can be aided by the use of relevant visualising tools. From the GPD (3.A.3), we have:

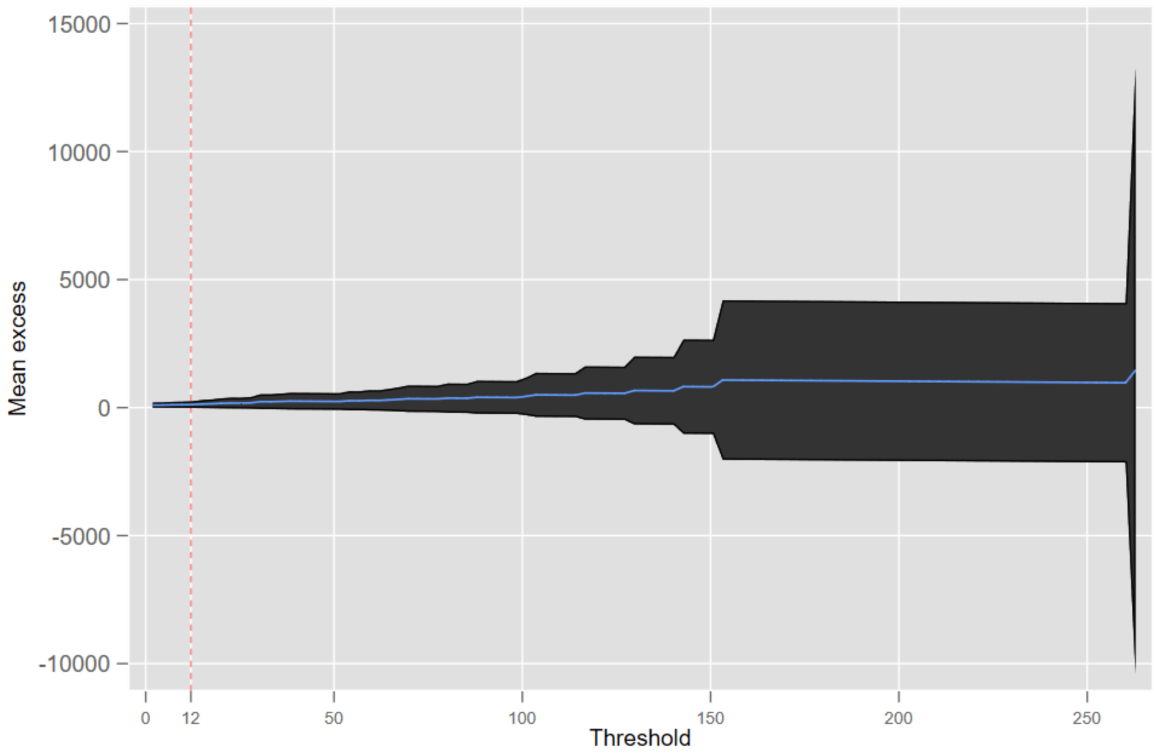
$$E\{X_{jk} - u_j | X_{jk} > u_j\} = \frac{\sigma_j + \xi_j(u_j - \mu_j)}{1 - \xi_j} \tag{3.A.4}$$

Note that $(\mu_j, \sigma_j, \xi_j)$ are the fixed parameters of the GEV $G_j(z)$ in (3.A.2). Thus, (3.A.4) is obviously a linear function of threshold $u_j$ as long as $u_j$ is large enough to make the asymptotic approximation behind the EVT to be valid. This motivates the use of the mean residual life plot (MRL), which visualises the relationship between the average of positive excesses corresponding to threshold $u_j$ and the threshold:

$$MRL = \left\{ \left( u_j, \frac{1}{n_{u_j}} \sum_{X_{jk} > u_j} (X_{jk} - u_j) \right) : u_j < X_j^{\max} \right\} \tag{3.A.5}$$

where $n_{u_j}$ is the number of all exceedances defined by the threshold $u_j$ in the dataset (all $X_{jt}$ exceeding the threshold $u_j$). The strategy is to pick the lowest threshold $u_j$, above which the MRL illustrates a reasonable line, taking into account the sample variations (i.e., incorporating the confidence intervals derived from the approximate normality of sample means). Once a reasonable threshold is obtained, the log-likelihood functions as detailed in Coles (2001) was adopted to estimate the pair of parameters $\hat{\xi}_j$ and $\hat{\tilde{\sigma}}_j$. It is noted that as long as the asymptotic approximation is valid ($u_j$ large enough), the shape parameter $\xi_j$ and the transformed scale parameter $\tilde{\sigma}_j^* = \tilde{\sigma}_j - \xi_j u_j = \sigma_j - \xi_j \mu_j$ are independent of the threshold $u_j$. This enables a post-estimation strategy to assess the selection of threshold $u_j$: to plot the estimates of $\xi_j$ and the transformed $\tilde{\sigma}_j$ against a range of corresponding $u_j$ and validate whether the estimates become stable when $u_j$ increases above the chosen threshold. Finally, the estimation can also be validated by a number of diagnostic plots including probability plot, quantile plot, return level plot ,and density plot (Coles, 2001). The first three plots compare the model-based and empirical estimates of the distribution function. The last one compares the density function of the fitted model with a histogram of the data. Figure 3.A.1 - 3.A.3 provide an example for the use of these graphs to select and verify the threshold and validate the POT model. The variable modelled in the example is (annual) human losses per 1 million heads in Mississippi (MS) caused by natural disasters. Similar graphs for other states and the other variable (economic loss) are available upon requests.

**Figure 3.A.1: Mean residual life plot**



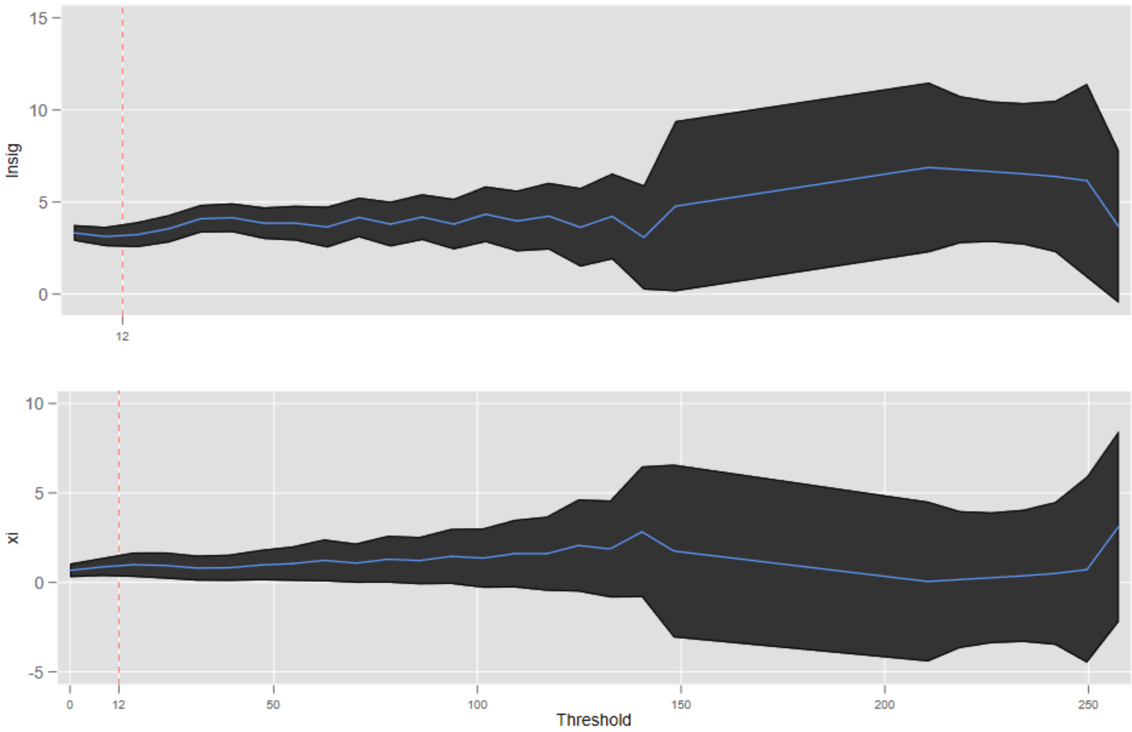

The figure provides an example for the use of Mean residual life plot (MRL) to support threshold selection. The variable modelled in the graph is (annual) human losses per 1 million heads in Mississippi (MS) caused by natural disasters. The threshold of 12 (red dotted line) is chosen as the the mean excesses above this point (blue line) seems to be reasonably linear once take into account the sample variations represented by the confidence interval (black area). Such a decision is supported by Figure 3.A.2 and validated by Figure 3.A.3.

Once we obtain the satisfactory ML estimates of the parameters $(\hat{\xi}_j; \hat{\sigma}_j)$, the N-year return level is estimated by:

$$\hat{z}_j(N) = u_j + \frac{\hat{\sigma}_j}{\hat{\xi}_j}[(N\hat{\zeta}_{u_j})^{\hat{\xi}_j} - 1] \qquad \text{for } \hat{\xi}_j \neq 0 \qquad (3.A.6)$$

$$\hat{z}_j(N) = u_j + \hat{\sigma}_j log(N\hat{\zeta}_{u_j}) \qquad \text{for } \hat{\xi}_j = 0 \qquad (3.A.7)$$

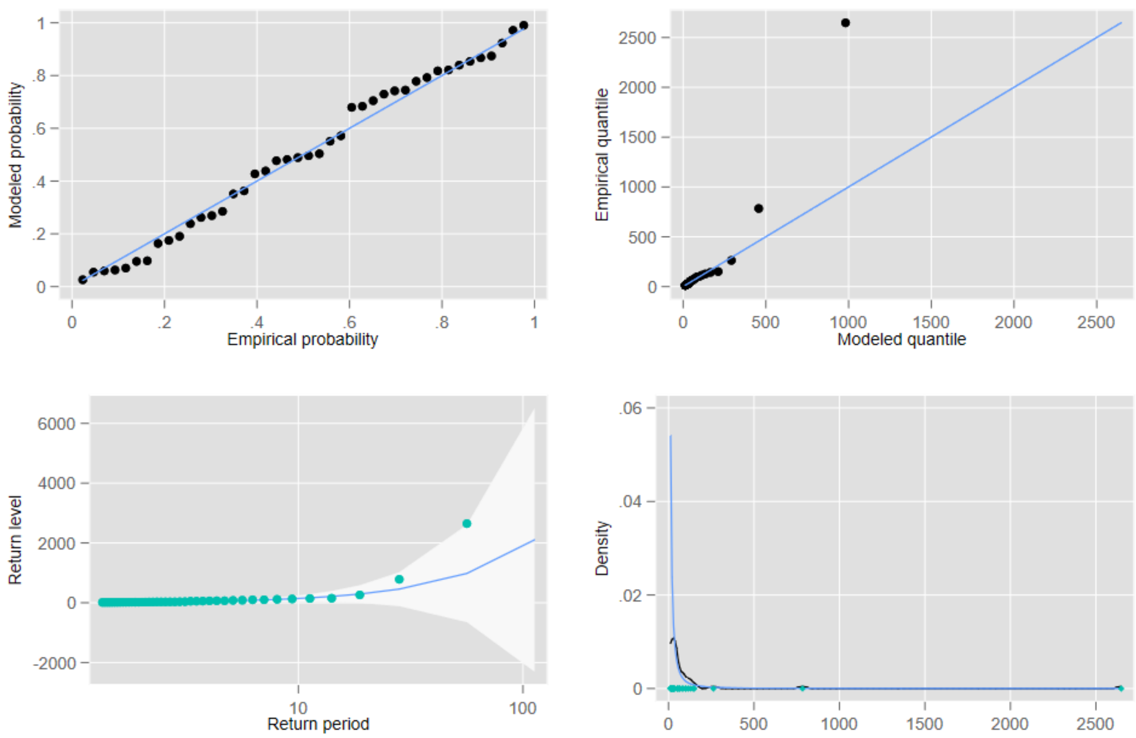
**Figure 3.A.2: POT parameter stability check**




The figure provides an example for the use of parameter stability plot to justify the threshold selection in Figure 3.A.1. The parameters (blue lines) including transformed scale parameter $\tilde{\sigma}^*$ (upper panel) and the shape parameter $\xi$ (lower panel) corresponding to a range of threshold values seem to be stable when the thresholds exceed the chosen value of 12 (red dotted line) once take into account the sample variations represented by the confidence interval (black area).

where $\zeta_{u_j}$ is the probability of an individual observation $X_{jt}$ greater than the threshold $u_j$ and can be estimated by the ratio between the number of observations in the sample that exceeding the chosen threshold ($k_j$) and the total observation number ($n_j$): $\hat{\zeta}_{u_j} = k_j/n_j$. The standard errors and confidence intervals of return levels can be computed by the delta method, taking into account the uncertainty due to $\zeta_{u_j}$ (Coles, 2001).

**Figure 3.A.3: POT and diagnosis plots**




The figure provides an example for diagnosis plots to verify the Peak Over a Threshold model given the threshold selected in Figure 3.A.1 and 3.A.2. The figure include the probability plot (up left), quantile plot (up right), return level plot (down left), and density plot (down right). See Coles (2001) for theoretical details about these plots.

# References


Abney, F. G. and Hill, L. B. (1966), 'Natural Disasters as a Political Variable: The Effect of a Hurricane on an Urban Election', *The American Political Science Review* **60**(4), 974–981.

Achen, C. H. and Bartels, L. M. (2004), 'Blind Retrospection. Electoral Responses to Drought, Flu, and Shark Attacks', *Estudio/Working Papers (Centro de Estudios Avanzados en Ciencias Sociales)* (199), 1.
**URL:** *http://www.march.es/ceacs/publicaciones/working/archivos/2004_199.pdf*

Americans for Democratic (2017), 'ADA Voting Records - Americans for Democratic Action'.
**URL:** *https://adaction.org/ada-voting-records/*

Anderson, W. L. and Mizak, D. A. (2006), 'Politics of environmental law: Political ideology, elitism or urban-rural interests?', *Public Choice* **129**(1-2), 131–157.

Arnold, R. D. (1990), *The Logic of Congressional Action*, Yale University Press.
**URL:** *http://www.jstor.org/stable/j.ctt32bm5b*

Atkin, E. (2017), 'Hurricane Harvey Could Also Be a Major Pollution Disaster | New Republic'.
**URL:** *https://newrepublic.com/article/144513/hurricane-harvey-also-major-pollution-disaster*

Auffhammer, M., Hsiang, S. M., Schlenker, W. and Sobel, A. (2013), 'Using weather data and climate model output in economic analyses of climate change', *Review of Environmental Economics and Policy* **7**(2), 181–198.

Bechtel, M. M. and Hainmueller, J. (2011), 'How Lasting Is Voter Gratitude? An Analysis of the Short- and Long-Term Electoral Returns to Beneficial Policy', *American Journal of Political Science* **55**(4), 852–868.

Birkland, T. A. (1996), 'Natural Disasters as Focusing Events: Policy Communities and Political Response', *International Journal of Mass Emergencies and Disasters* **14**(2), 221–243.

Birkland, T. A. (2016), 'Policy Process Theory and Natural Hazards', **1**(May 2018), 1–26.
**URL:** *http://naturalhazardscience.oxfordre.com/view/10.1093/acrefore/9780199389407.001.0001/acrefore-9780199389407-e-75*

Boscarino, J. E. (2009), 'Surfing for problems: Advocacy group strategy in U.S. forestry policy', *Policy Studies Journal* **37**(3), 415–434.

Botzen, W. J. W., Michel-Kerjan, E., Kunreuther, H., de Moel, H. and Aerts, J. C. J. H. (2016), 'Political affiliation affects adaptation to climate risks: Evidence from new york city', *Climatic Change* **138**(1), 353–360.
**URL:** *https://doi.org/10.1007/s10584-016-1735-9*

Canes-Wrone, B., Minozzi, W. and Reveley, J. B. (2011), 'Issue accountability and the mass public', *Legislative Studies Quarterly* **36**(1), 5–35.

Chupp, B. A. (2011), 'Environmental Constituent Interest, Green Electricity Policies, and Legislative Voting', *Journal of Environmental Economics and Management* **62**(2), 254–266.
**URL:** *http://dx.doi.org/10.1016/j.jeem.2011.03.008*

Clinton, J. D. (2006), 'Representation in congress: Constituents and roll calls in the 106th House', *Journal of Politics* **68**(2), 397–409.

Coles, S. (2001), *An Introduction to Statistical Modeling of Extreme Values*, 3rd edn, Springer-Verlag London limited 2001, London.

Colman, Z. (2017), 'Harvey 'historic' to Trump, but scientists see new norm', *E&E News* .
**URL:** *https://www.eenews.net/greenwire/stories/1060059383/*

Colman, Z. (2018), 'Federal Government' s Silence on Climate Could Stymie Disaster Planning', *Sciencetific American* .
**URL:** *https://www.scientificamerican.com/article/federal-governments-silence-on-climate-could-stymie-disaster-planning/*

Dart, T., Carroll, R. and Lartey, J. (2018), 'Explosions at flooded Texas chemical plant leave confusion over toxic risk', *The Guardian* .
**URL:** *https://www.theguardian.com/us-news/2017/aug/31/explosions-flooded-texas-chemical-plant-arkema-crosby*

Estrada, F., Botzen, W. J. W. and Tol, R. S. J. (2015), 'Economic losses from US hurricanes consistent with an influence from climate change', *Nature Geoscience* **8**, 880.
**URL:** *http://dx.doi.org/10.1038/ngeo2560 http://10.0.4.14/ngeo2560 https://www.nature.com/articles/ngeo2560#supplementary-information*

Ferris, A., Garbaccio, R., Marten, A. and Wolverton, A. (2017), The Impacts of Environmental Regulation on the U.S. Economy.
**URL:** *https://www.epa.gov/environmental-economics*

Fisher, R. A. and Tippett, L. H. C. (1928), 'Limiting forms of the frequency distribution of the largest or smallest member of a sample', *Mathematical Proceedings of the Cambridge Philosophical Society* **24**(02), 180.
**URL:** *http://www.journals.cambridge.org/abstract_S0305004100015681*

Flavelle, C. (2018), 'FEMA Strips Mention of 'Climate Change' From Its Strategic Plan', *Bloomberg* .
**URL:** *https://www.bloomberg.com/news/articles/2018-03-15/fema-strips-mention-of-climate-change-from-its-strategic-plan*

Friedman, L. (2017), 'Congressional Auditor Urges Action to Address Climate Change', *The New York Times* .
**URL:** *https://nyti.ms/2h3pQ5z*

Garand, J. C. (2010), 'Income inequality, party polarization, and roll-call voting in the U.S. Senate', *Journal of Politics* **72**(4), 1109–1128.

Garrett, T. A. and Sobel, R. S. (2003), 'The political economy of FEMA disaster payments', *Economic Inquiry* **41**(3), 496–509.

Gasper, J. T. and Reeves, A. (2011), 'Make It Rain? Retrospection and the Attentive Electorate in the Context of Natural Disasters', *American Journal of Political Science* **55**(2), 340–355.

Goddard, L. and Dilley, M. (2005), 'El nino: catastrophe or opportunity', *Journal of Climate* **18**(5), 651–665.

Goodstein, E. B. (1994), *Jobs and the Environment*, Economic Policy Institute, Washington D.C.

Gupta, A. K. and Nair, S. S. (2012), Environmental Legislation for Disaster Risk Management, Module-I.
**URL:** *http://www.preventionweb.net/files/30127_30127legal1.pdf*

Hazards & Vulnerability Research Institute (2015), 'Spatial Hazard Events and Losses Database for the United States, Version 14.0. [Online Database].'.
**URL:** *http://hvri.geog.sc.edu/SHELDUS/index.cfm?page=metadata*

Healy, A. and Malhotra, N. (2009), 'Myopic voters and natural disaster policy', *American Political Science Review* **103**(3), 387–406.

Jenkinson, A. F. (1955), 'The frequency distribution of the annual maximum (or minimum) values of meteorological elements', *Quarterly Journal of the Royal Meteorological Society* **81**(348), 158–171.
**URL:** *http://doi.wiley.com/10.1002/qj.49708134804*

Kahn, M. E. (2007), 'Environmental disasters as risk regulation catalysts? The role of Bhopal, Chernobyl, Exxon Valdez, Love Canal, and Three Mile Island in shaping U.S. environmental law', *Journal of Risk and Uncertainty* **35**(1), 17–43.

Kahn, M. E. and Kotchen, M. J. (2010), Environmental Concern and the Business Cycle: The Chilling effect of recession.

Labadie, J. R. (2006), Environmental Management and Disasters : Contributions of the Discipline to the Profession and Practice of Emergency Management, *in* D. A. McEntire, ed., 'Disciplines, Disasters and Emergency Management: The Convergence and Divergence of Concepts, Issues and Trends from the Research Literature', FEMA Emergency Management Institute, chapter 20, pp. 260–271.
**URL:** *https://training.fema.gov/hiedu/aemrc/booksdownload/ddemtextbook/*

League of Conservation Voters (2018), 'National Environmental Scorecard'.
**URL:** *http://scorecard.lcv.org/scorecard?year=all*

Lee, D. S., Moretti, E. and Butler, M. J. (2004), 'Do Voters Affect or Elect Policies? Evidence from the U. S. House', *The Quarterly Journal of Economics* **119**(3), 807–859.
**URL:** *https://academic.oup.com/qje/article-lookup/doi/10.1162/0033553041502153*

Lewis, J. B., Poole, K., Rosenthal, H., Boche, A., Rudkin, A. and Sonnet, L. (2017), 'Voteview: Congressional Roll-Call Votes Database'.
**URL:** *https://voteview.com/*

Malhotra, N. and Kuo, A. G. (2008), 'Attributing blame: The public's response to Hurricane Katrina', *Journal of Politics* **70**(1), 120–135.

Mckibben, B. (2017), 'The Trump administration's solution to climate change: ban the term', *The Guardian* .
**URL:** *https://www.theguardian.com/commentisfree/2017/aug/08/trump-administration-climate-change-ban-usda*

Meyer, S. (2002), 'The Economic Impact of Environmental Regulation', *International Journal of Social Economics* **29**(7), 538–546.
**URL:** *http://www.emeraldinsight.com/10.1108/03068290210431560*

Miler, K. (2016), 'Legislative Responsiveness to Constituency Change', *American Politics Research* **44**(5), 816–843.

Mooney, C. and Dennis, B. (2018), 'Extreme hurricanes and wildfires made 2017 the most costly U.S. disaster year on record', *Washington Post* .
**URL:** *https://www.washingtonpost.com/news/energy-environment/wp/2018/01/08/hurricanes-wildfires-made-2017-the-most-costly-u-s-disaster-year-on-record/?utm_term=.cc1ad5a0e061*

Natter, A. and Calkins, L. B. (2018), 'Harvey Responders Say the Arkema Plant Blaze Made Them Sick', *Bloomberg* .
**URL:** *https://www.bloomberg.com/news/articles/2017-09-07/harvey-responders-say-they-were-sickened-by-arkema-plant-blaze*

NOAA (2014), 'ClimDiv STATEWIDE-REGIONAL-NATIONAL TEMPERATURE-PRECIPITATION-DROUGHT'.
**URL:** *https://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/state-readme.txt*

NOAA National Hurricane Center (2018), 'Costliest U.S. tropical cyclones tables updated NOAA's'.
**URL:** *https://www.nhc.noaa.gov/news/UpdatedCostliest.pdf*

Pickands, J. (1975), 'Statistical inference using extreme order statistics', *The Annals of Statistics* **3**(1), 119–131.
**URL:** *http://www.jstor.org/stable/2958083*

Poole, K. T. (2005), *Spatial models of parliamentary voting*, Cambridge University Press.

Poole, K. T. and Rosenthal, H. (1985), 'A Spatial Model for Legislative Roll Call Analysis', *American Journal of Political Science* **29**(2), 357–384.

Poole, K. T. and Rosenthal, H. (2007), *Ideology and Congress*, Transaction Publishers.
**URL:** *https://books.google.co.uk/books/about/Ideology_and_Congress.html?id=eOuZqa7UbqUC&redir_esc*

Ringquist, E. J. and Dasse, C. (2004), 'Lies, damned lies, and campaign promises? Environmental legislation in the 105th congress', *Social Science Quarterly* **85**(2), 400–419.

Tanger, S. M., Zeng, P., Morse, W. and Laband, D. N. (2011), 'Macroeconomic conditions in the U.S. and congressional voting on environmental policy: 1970-2008', *Ecological Economics* **70**(6), 1109–1120.
**URL:** *http://dx.doi.org/10.1016/j.ecolecon.2010.12.021*

UNEP (2007), *Environment and disaster risk - Emerging Perspectives*.

Vandeweerdt, C., Kerremans, B. and Cohn, A. (2016), 'Climate voting in the US Congress: the power of public concern', *Environmental Politics* **25**(2), 268–288.
**URL:** *http://dx.doi.org/10.1080/09644016.2016.1116651*

Vose, R. S., Applequist, S., Squires, M., Durre, I., Menne, C. J., Williams, C. N., Fenimore, C., Gleason, K. and Arndt, D. (2014), 'Improved historical temperature and precipitation time series for U.S. climate divisions', *Journal of Applied Meteorology and Climatology* **53**(5), 1232–1251.

Wolff, E. (2017), 'Energy Department climate office bans use of phrase 'climate change'', *Politico* .
**URL:** *www.politico.com/story/2017/03/energy-department-climate-change-phrases-banned-236655*

Wouter Botzen, W. J. and Van Den Bergh, J. C. J. M. (2012), 'Monetary valuation of insurance against flood risk under climate change', *International Economic Review* **53**(3), 1005–1026.
**URL:** *https://doi.org/10.1111/j.1468-2354.2012.00709.x*

# Conclusions, Limitations and Future Research

This thesis provides evidence on the multidimensional relationship between the environment and human activities in two domains, economics and politics. These processes could both support and compete each others and their linkages tend to change over space and time.

Chapter 1 indicates that when proper policies are adopted, humans are able to harness natural resources to benefit their society while still living peacefully with the environment. Indeed, the national system of large hydropower dams in Vietnam not only supplies clean power for the economy to get out of poverty and thrive but also protects its people from extreme weathers such as floods and droughts. The cascade design is shown to strengthen the resilience of such a system against weather shocks, which is important for a country like Vietnam that is considered to be among the most vulnerable to climate change. Vietnam's experience can be helpful for other economies where hydropower potential remain underexploited and power supply is still a constraint to the development.

Chapter 2 however shows that policies need to be frequently reviewed and updated to take into account the possible changes in natural and social processes. The abundance of untapped power sources in the past (such as hydropower, coal, and gas reserves), and the relatively low dependency of simple businesses on power quality allowed Vietnam's growth to benefit from a rapid expansion of an inefficient and unreliable power system. However, as shown in this chapter firms have become more vulnerable to power disruption, and as we show this is because they have moved up the supply chain, where simple assembly, and processing are replaced by more comprehensive manufacturing processes, that, with machinery and energy, are used more intensively to generate higher value added. Under such circumstances, the improvement in power quality is essential to support growth. Given the exhaustion of traditional power sources (the almost full exploitation of hydropower and and the more reliance on imports of coal), this task means that Vietnam needs to adopt legal reform to liberalise the market and promote new technology to harness new power sources (wind, solar, nuclear), increase the reliability of current system (construct facility for pumped-storage hydropower and upgrade the transmission and distribution system) and promote power saving technology.

Chapter 3 sheds light on how law is made to protect the environment under an established democratic setting. Similar to previous studies, it confirms that ideology is a prominent factor that decides how legislators vote for environmental issues at the US's Senate. However, there is still a role for their response to an exogenous shock in their constituencies such as unanticipated immense damages by natural disasters, though the effect is slow in coming (two years) and short-lived (one year), probably due to bounded rationality of the legislators. Yet, activists may find an opportunity in the occurrence of a natural disaster to draw public attention to environmental issues and call for more stringent regulations that could prevent future environmental degradation, which contributes to the vulnerability to natural disasters, and reduces the consequences of environmental disasters triggered by natural disasters.[27] However our empirical findings suggest that senators vote more for such stringency after natural disasters only if they cause extreme losses in terms of human suffering. If disasters damage the economy instead, their votes becomes less friendly to the environment. This may reflect the concern that strict regulation could put further restriction on businesses, where the interests in economic recovery and redevelopment are prioritised.

[27] For example, low carbon policies may help with the issues of changing climate, which is deemed to be associated with increasing frequencies and damages of weather-related events such as wildfires, floods, hurricanes. Another example is that strict regulations may help prevent oil spills or pollutant releases after flooding.

# Limitations

While we attempt to use high-quality datasets from reliable sources, and adopt the advanced research designs to gain robust findings, this research is not free from limitations. This section will discuss some of the key issues.

For chapter 1, the scope of analysis is restricted among large hydropower dams only as consistent data on medium and small dams were not available. Therefore, one should interpret the results of this study with prudence and not overgeneralise our findings.[28] In addition, there are also a number of simplifications in our rainfall-runoff model (SWAT) such as we were not able to take into account the construction and operation of hydropower dams upstream from Vietnam, changes in land cover, the transportation of sediment load and the degradation of soil. These factors together with measurement errors in the original data may not be fully offset by the fixed effects and hence bias the regression results though the direction of the potential biasness remains unknown. In addition, should we have been able to better calibrate the rainfall-runoff model, the simulated flows should be fit for the real flows and thus be a more reliable proxy for the power generation regression. Finally, we need to acknowledge that our flood measure is relatively coarse and is not able to capture all aspects of floods in a monsoon context (to be able to differentiate the impacts of beneficial vs disaster floods) and our static model of flood control benefit is not appropriate to model the long run impact.

For chapter 2, our analysis is largely dependent on the quality of two World Bank Enterprises Surveys though it could be not strictly comparable between two waves 2005 and 2015. In addition, the limited access to distribution and transmission data generates a substantial source of uncertainty in our estimates though we try to partially mitigate the issue by capturing it in a distance penalty parameter and analysing the sensitivity of our results to the changes in such a parameter.

[28] Different from large dams, there are a number of problems with the construction and operation of medium and small dams due to a lack of effective supervision and regulation (PanNature, 2010; Le and Dao, 2016). For example, flood control function could be squeezed for power generation purpose as only the later creates profit for dam owners. The cooperation between dams in cascade is also a big question.

For chapter 3, we establish the causal relationship between natural disaster and senatorial voting behaviour by identifying the important natural disaster event years and rest on the assumption that the distribution of possible losses is identical over 55 years (1960-2014) of our sample period and there is no temporal clustering of events. Such an assumption could be arguably less unrealistic and should be validated by properly explicit modelling when longer data is available.

# Future Research

The framework in chapter 1 can be extended in a number of ways. First, when the rainfall-runoff is properly calibrated, the model is appropriate to link with climate change scenario data to simulate the operation of large dams in Vietnam under different conditions of changing climate. Second, if more data on hydropower dams were to become available for countries outside Vietnam, for example Mekong Region countries, our framework has the potential to evaluate how dams in upstream countries affect downstream ones and as a such support the international attempt to coordinate trans-boundary water resources management. Third, our framework may be useful to evaluate the impact of other factors on hydropower generation, such as land cover change, soil degradation and sediment transportation. Finally, the framework can be linked with data for water demand and usage to better analyse the irrigation function of large dams.

The framework in chapter 2 can be extended to panel data set up if applicable, for example by combining annual firm surveys by General Statistics Office (GSO) and power reliability indices (SAIDI/SAIFI) for province level, though the credibility of these indices if accessible need further investigation. It is also desirable to incorporate more information on power transmission and distribution to achieve more robust findings.

Finally, it could be interesting to replicate the study in chapter 3 for the House of Representatives. The shorter tenure of representatives mean that natural disasters could have stronger impact on their voting patterns, though the direction is not totally clear. A main challenge for such a study probably is to model the distribution of natural disasters when the constituency boundary changes over time due to redistricting. The approach is also relevant for the examination of other countries to better understand the democracy.

## References


Le, A. T. and Dao, T. V. N. (2016), *Hydropower developement in Vietnam: Challenges and solutions*, Science and Technology Publisher, Ha Noi, Vietnam.

PanNature (2010), 'Small and medium hydropower: Great impacts on environment but less supervision of environmental impact assessment'.
**URL:** *http://www.nature.org.vn/en/2010/07/small-and-medium-hydropower-impacts-on-environment/*